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EAG Laboratories

Automatic Critical Dimension Measurements Enabled by Deep Learning

Deep learning methods for image segmentation enable accurate critical dimension measurements from images with complex contrast patterns.

Introduction

Critical dimension measurements are a key part of micro- and nano-scale solid state device characterization. Whether it is an electronic device in a semiconductor chip or a nanopore for DNA sequencing, critical dimensions often determine the overall performance and yield of the device during manufacturing. Utilizing image processing to analyze microscopy images is a common method for automatically performing critical dimension measurements. Transmission electron microscopy (TEM) is the primary tool used to image devices when nanoscale spatial resolution is required. However, there are a variety of mechanisms that generate contrast in TEM images, including diffraction, chemical composition, sample thickness, zone-axis alignment, and image defocus, all of which combine to generate the final image. This can make it very difficult to write a metrology recipe to automate critical dimension measurements using only conventional image processing. Although scanning transmission electron microscopy and spectroscopy techniques may provide signals that are easier to interpret or process [1], their acquisition speeds are significantly slower than regular TEM imaging. These issues and trade-offs are not unique to TEM; similar complexities can affect scanning electron microscopy and optical microscopy as well.

In this application note, we highlight how deep learning methods for image segmentation, such as convolutional neural networks (CNNs) or vision transformers, can help interpret the complex contrast of TEM images and segment a series of thin films in 3D NAND devices. This enables us to make accurate critical dimension measurements and extract the maximum amount of insight from the TEM dataset. Although we focus on an example from the semiconductor industry here, this process can be applied to devices for any application.

Data Collection and Processing

The development and application process for a deep-learning-based metrology recipe is illustrated in Figure 1. The first step in development is to collect and annotate a set of training images from the 3D NAND device. As much as possible, the dataset should cover the full breadth of the possible images that the metrology recipe is expected to handle; all significant features of the sample should be represented in the training data. The process of annotating the images involves manually labeling/drawing the regions that the model needs to identify in the training images. Although this process can be time consuming, there are ways to speed up the process. If automation is requested as part of an ongoing/recurring imaging job, then past data can be utilized, and new training images do not need to be collected. Conventional image processing can also help generate approximate annotations which are then refined manually. Most importantly, the training dataset only needs to be fully compiled and annotated once at the start of the development process. The initial training dataset can be supplemented with smaller datasets as the samples submitted evolve over time, but the full process does not need to be repeated.

Once an annotated training dataset is ready, we can use it to train a neural network model to perform the segmentation automatically. As a part of the training process, we can experiment with different types of neural networks and adjustments to the training parameters to optimize the model's performance and ensure it generates results that will be most useful when writing the metrology recipe. Once the model is trained, we can integrate it into a metrology recipe to perform the requested critical dimension measurements. The recipe will use both results from the neural network and conventional image processing techniques, such as filtering and thresholding, to draw the critical dimension measurements in the correct position. Combining both deep learning and conventional processing ensures that the measurements will match the features in the image as closely as possible and that the measurements can be adjusted based on feedback from engineers or the customer without fully retraining the model.

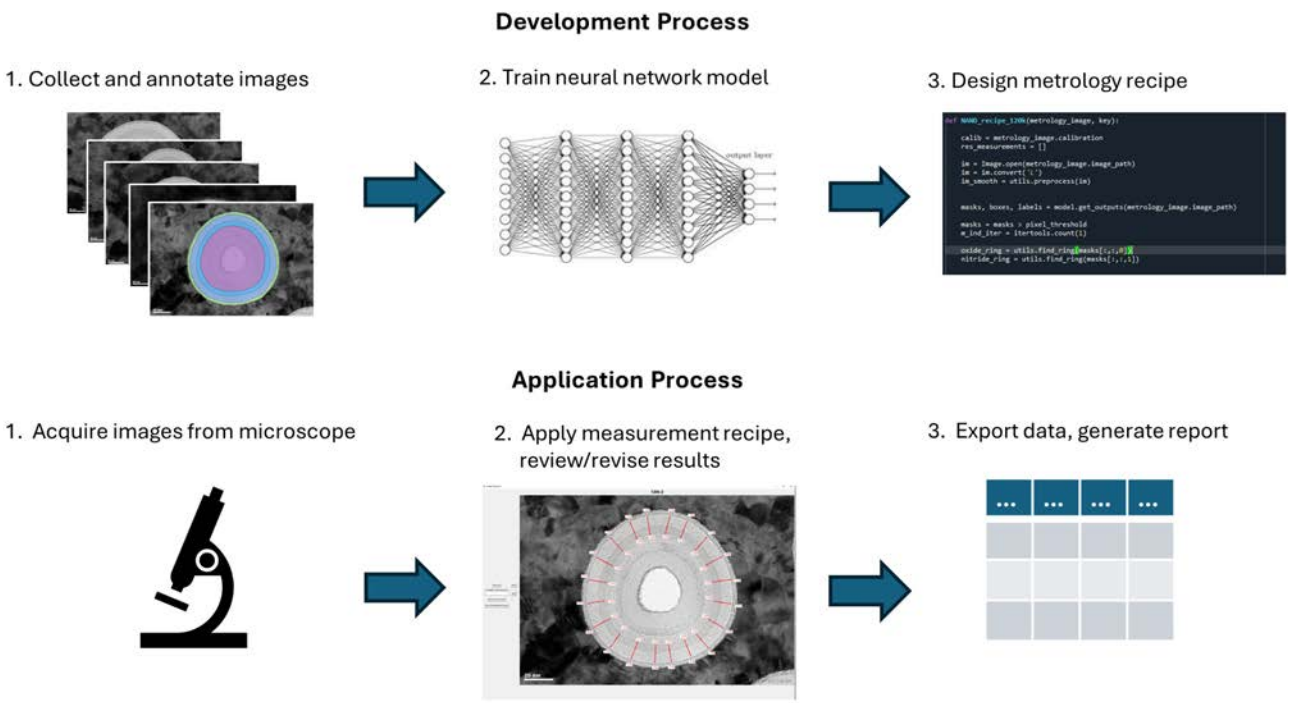


Figure 1. An illustration of the development and application process for deep learning-based metrology recipe.

After the metrology recipe is written, it can be loaded into EAG's automated metrology application so that engineers and technicians can apply it to images from new incoming samples. Once a recipe is applied to an image, the measurements can be adjusted and reviewed interactively by an engineer to ensure every measurement is accurate. For some structures, fully automated recipes can also be used to generate measurements. From here we can create a customized report and calculate statistics from large sets of measurements depending on the customer's request. Report formatting can even be tailored to work with the customer's own internal data analysis tools.

Figure 2 illustrates the segmentation results from training a vision transformer model on the dataset from a 3D NAND sample. Figure 2a shows an example image of a 3D NAND capacitor with each layer labeled. We focused on the Al_2O_3/TiN liner, blocking oxide, and the nitride storage layers. These layers would be particularly difficult to segment by conventional image processing due to their close intensity values, noisy texture caused by the amorphous atomic structure, and weak interface contrast. The inner interface of the nitride storage layer can often be especially difficult to discern visually as seen in some regions of Figure 2a. Although this may present some uncertainty when annotating individual training images, the training process allows the model to learn the subtle general patterns that differentiate these layers. This enables the model to provide consistent segmentations that best fit the entire training dataset even when there may be random annotation errors in individual images. The segmentation masks covering each layer generated by our model are shown in Figure 2b. For this application note, we annotated a total of 53 images, with 10 reserved for validation and testing, and trained a variation of the Multi-scale Attention Network (MA-Net) model [2] to perform the semantic segmentation. We have also trained a Unet model [3] using an EfficientNet feature extractor [4] on this same dataset and achieved comparable results. The required size of the training dataset depends on the complexity and variation in the images being analyzed, but a typical training dataset consists of at least 50-100 images. Other types of models, such as instance segmentation, may be used if necessary.

The image in Figure 2a is from the reserved testing set, so the model was not shown this image during the training process. Having enough images to reserve for validation and testing is important to ensure the model will perform well on new images/ samples it has never seen before. Small errors in the segmentation mask that may appear when the model is applied to new images can be eliminated with a few post-processing steps.

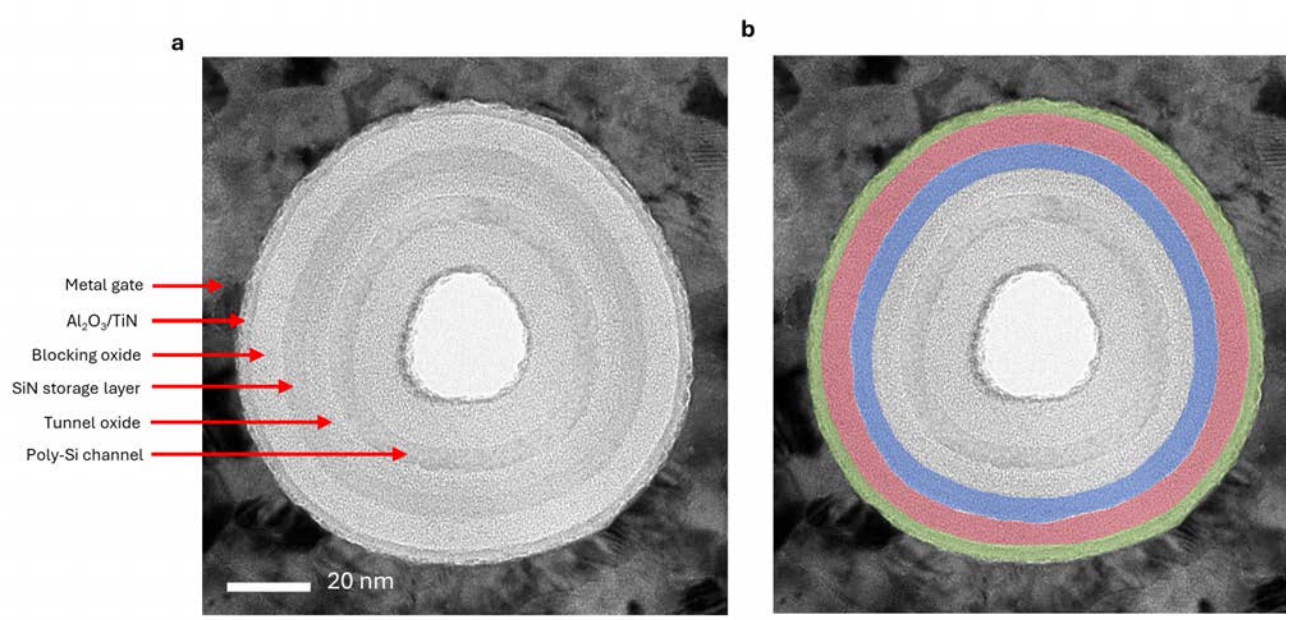


Figure 2. ***a*** *TEM image of a 3D NAND structure from a planview lamella.*
b *Segmentation masks for the Al2O3/TiN (green), blocking oxide (red), and nitride storage (blue) layers generated by the vision transformer model.*

For the 3D NAND capacitor, we can employ the masks shown in Figure 2b to develop various metrology recipes using the model for the measurements of individual layers and the whole structure. Figure 3a illustrates an interactive recipe that makes a moderate number of thickness measurements of both the nitride and oxide layers. These measurements are first estimated based on the mask from the model and adjusted based on image contrast. Then they are presented to the engineer for manual adjustment and can then be exported in the customer's desired format. Figure 3b shows a case where the outer perimeter of the Al_2O_3/TiN mask is extracted to measure the major (red) and minor (blue) axes of the 3D NAND structure. Figure 3c shows how the nitride layer mask can be used to automatically generate high density thickness measurements. This approach relies more heavily on the accuracy of the model and measurement recipe as the number of measurements would be impractical for an engineer to review manually. But it is an effective strategy for generating a large dataset of critical dimension measurements that may be useful for downstream analysis. Although we have focused on thickness/distance measurements in these images, we can also measure other types of values including the angles, curvatures, slopes, and fitted parameters as required.

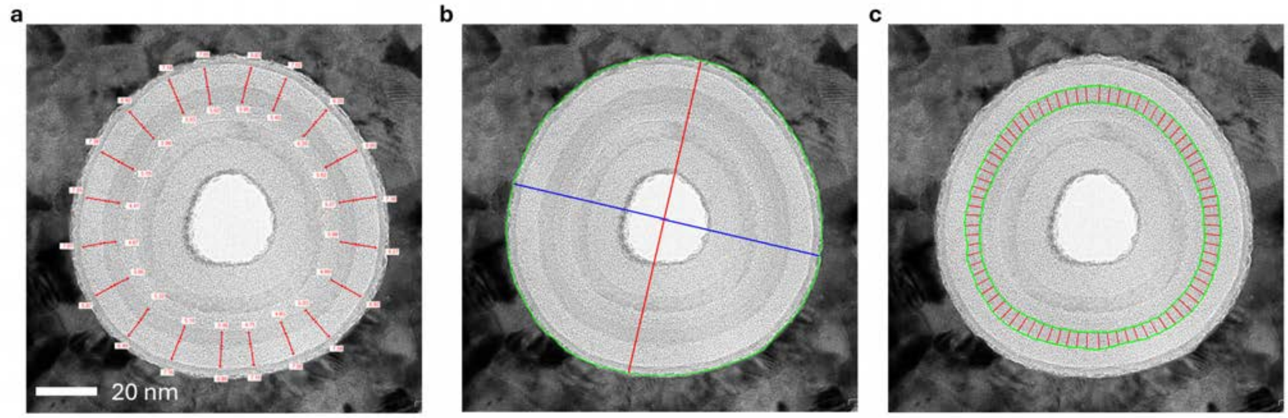


Figure 3. ***a*** *Results from a metrology recipe that measures the thickness of the oxide and nitride layers, optimized for manual review.*
b *A metrology recipe that measures the major/minor axes of the 3D NAND structure.*
c *A metrology recipe that makes high density measurements of the nitride thickness, optimized for fully automated analysis.*

Images can also contain multiple objects within the field of view, as shown in Figure 4, or more complex structures which can be broken down into component parts for analysis. EAG will work with the customer to collaboratively design a segmentation strategy and metrology recipe to fit any requested structure and set of measurements.

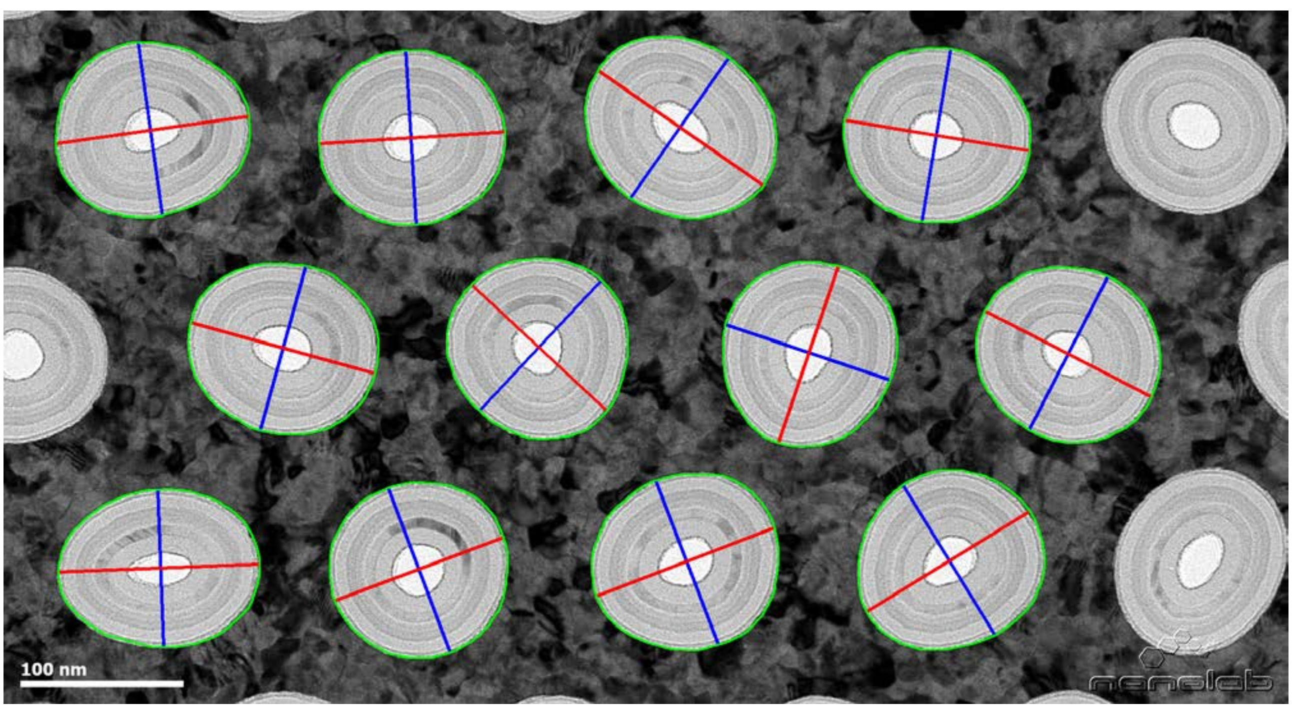
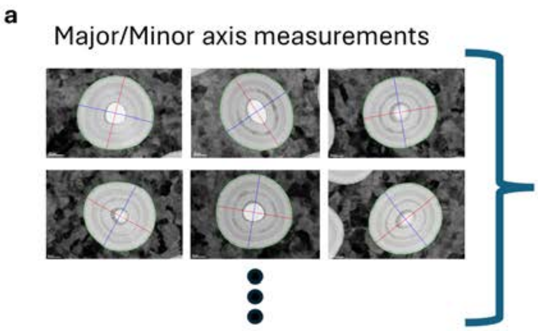


Figure 4. Major/minor axis measurements on multiple 3D NAND structures within the same field-of-view.

EAG can also summarize and visualize the critical dimension measurements to help our customers understand their samples. Tabular data can be exported in the requested format and summarized with various statistical quantities. In the example in Figure 5a, we have calculated some basic statistics of the major and minor axes from the whole 3D NAND dataset. In addition, we can calculate any compound values requested. For example, here we have calculated the circularity which is defined as the ratio of the minor axis to the major axis. In the example in Figure 5b, we used the high-density nitride layer measurements to study the film thickness in detail. The polar plot shows the thickness variation as a function of position around the 3D NAND structure and the histogram shows the full distribution of thickness measurements.



Minor axis mean (nm)	Minor axis St. dev. (nm)	Major axis mean (nm)	Major axis St. dev. (nm)	Mean circularity
102.12	3.65	111.50	2.95	0.92

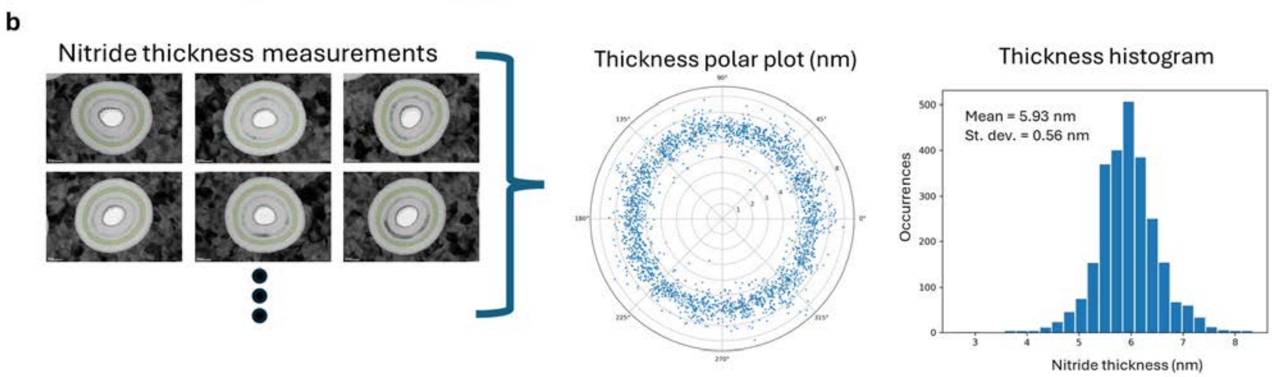


*Figure 5. **a** An illustration of how tabular data can be summarized.*
***b** An illustration of the types of visualizations that we can generate from a large dataset.*

Conclusion

Automatic metrology is an essential tool in process and yield control for solid state devices. In this application note, we have outlined how deep learning can enhance the metrology process to deliver accurate automatic critical dimension measurements in cases where conventional image processing may struggle. By training a vision transformer model to segment regular TEM images of a 3D NAND structure, we can build metrology recipes that generate a variety of critical dimension measurements. This enables us to utilize the fastest imaging mode available in TEM and collect as much information as possible from the resulting images. The process illustrated here can be applied to any type of imaging data including x-ray, optical, and electron microscopy. Eurofins EAG provides our customers with access to state-of-the-art microscopy facilities and expertise to deliver the highest quality imaging data. As demonstrated here, we also offer customized quantitative image and data processing solutions to help our customers extract the most actionable knowledge out of their data and solve their most challenging materials science problems. Contact us today to learn how we can help with your next project.

References

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