

GENERATING SYNTHETIC MICROSPY IMAGES OF MANUFACTURED DEVICES

TECHNICAL FIELD

[001] The present disclosure relates to methods associated with machine learning models used for assessment of manufactured devices, such as semiconductor devices. More particularly, the present disclosure relates to methods for generating and utilizing synthetic microscopy image data with machine learning models associated with devices processed by processing equipment.

BACKGROUND

[002] Products may be produced by performing one or more manufacturing processes using manufacturing equipment. For example, semiconductor manufacturing equipment may be used to produce substrates via semiconductor manufacturing processes. Products are to be produced with particular properties, suited for a target application. Machine learning models are used in various process control and predictive functions associated with manufacturing equipment. Machine learning models are trained using data associated with the manufacturing equipment. Images of products (e.g., manufactured devices) may be taken, which may enhance understanding of device function, failure, performance, may be used for metrology or inspection, or the like.

SUMMARY

[003] The following is a simplified summary of the disclosure in order to provide a basic understanding of some aspects of the disclosure. This summary is not an extensive overview of the disclosure. It is intended to neither identify key or critical elements of the disclosure, nor delineate any scope of the particular embodiments of the disclosure or any scope of the claims. Its sole purpose is to present some concepts of the disclosure in a simplified form as a prelude to the more detailed description that is presented later.

[004] In one aspect of the present disclosure, a method includes receiving data indicating a plurality of dimensions of a manufactured device. The method further includes providing the data to a trained machine learning model. The method further includes receiving, from the trained machine learning model, a synthetic microscopy image associated with the manufactured device, wherein the synthetic microscopy image is generated in view of the first data. The method further includes performing at least one of (i) outputting the

synthetic microscopy image to a display or (ii) performing one or more operations on the synthetic microscopy image.

[005] In another aspect of the disclosure, a method includes receiving a plurality of microscopy images of a plurality of manufactured devices. The method further includes receiving data indicating a plurality of dimensions of the plurality of manufactured device. The method further includes training a machine learning model, wherein training the machine learning model includes providing the first data to the machine learning model as training input. The training further includes providing the plurality of microscopy images to the machine learning model as target output.

[006] In another aspect of the disclosure, a non-transitory machine-readable storage medium is disclosed. The storage medium stores instructions which, when executed, cause a processing device to perform operations. The operations include receiving data indicating a plurality of dimensions of a manufactured device. The operations further include providing the data to a trained machine learning model. The operations further include receiving, from the trained machine learning model, a synthetic microscopy image associated with the manufactured device. The synthetic microscopy image is generated in view of the first data. The operations further include performing at least one of (i) outputting the synthetic microscopy image to a display or (ii) performing one or more operations on the synthetic microscopy image.

BRIEF DESCRIPTION OF THE DRAWINGS

[007] The present disclosure is illustrated by way of example, and not by way of limitation in the figures of the accompanying drawings.

[008] FIG. 1 is a block diagram illustrating an exemplary system architecture, according to some embodiments.

[009] FIGS. 2A-B depict block diagrams of example data set generators for creating data sets for models, according to some embodiments.

[0010] FIG. 3 is a block diagram illustrating a system for generating output data, according to some embodiments.

[0011] FIGS. 4A-B are flow diagrams of methods associated with generating and utilizing one or more machine learning models for generating synthetic image data, according to some embodiments.

[0012] FIG. 4C is a flow diagram of a method for generating and using synthetic microscopy image data, according to some embodiments.

[0013] FIGS. 5A-B are block diagrams of example machine learning architecture for generating synthetic data, according to some embodiments.

[0014] FIGS. 5C-D are flow diagrams of methods associated with training and using machine learning models for generating synthetic image data from cartoon images, according to some embodiments.

[0015] FIG. 5E is an example cartoon image of a manufactured device, according to some embodiments.

[0016] FIG. 6 is a block diagram illustrating a computer system, according to some embodiments.

DETAILED DESCRIPTION

[0017] Described herein are technologies related to generating synthetic microscopy images of manufactured products. Manufacturing equipment is used to produce products, such as substrates (e.g., wafers, semiconductors). Manufacturing equipment may include a manufacturing or processing chamber to separate the substrate from the environment. The properties of produced substrates are to meet target values to facilitate specific functionalities. Manufacturing parameters are selected to produce substrates that meet the target property values. Many manufacturing parameters (e.g., hardware parameters, process parameters, etc.) contribute to the properties of processed substrates. Manufacturing systems may control parameters by specifying a set point for a property value and receiving data from sensors disposed within the manufacturing chamber, and making adjustments to the manufacturing equipment until the sensor readings match the set point. In some embodiments, trained machine learning models are utilized to improve performance of manufacturing equipment.

[0018] Machine learning models may be applied in several ways associated with processing chambers and/or manufacturing equipment. A machine learning model may receive as input sensor data, measuring values of properties in a processing chamber. The machine learning model may be configured to predict process results, e.g., metrology results of the finished product. A machine learning model may receive as input in-situ data associated with the work piece or substrate (e.g., reflectance spectroscopy of a semiconductor wafer during an etch process) and/or ex situ data (e.g., metrology data associated with the work piece or substrate). The machine learning model may be configured to predict and control process results, e.g., may predict when an etch process is completed and send instructions to the processing chamber to stop the etch operation. The machine learning

model may additionally or alternatively be configured to estimate one or more properties (e.g., such as critical dimensions) of manufactured devices on a substrate or work piece. In some embodiments, a machine learning model may accept as input metrology data of a substrate (e.g., generated after a process is complete) and/or in situ data of the substrate (e.g., generated during a manufacturing process). The metrology data and/or in-situ data may be data that is generally collected with or without damaging the substrate. Many metrology measurements, such as those performed by cross sectioning imaging tools including cross-sectional scanning electron microscopy (XSEM) or transmission electron microscopy (TEM), are destructive and damage the substrate. The machine learning model may be configured to produce as output estimations or predictions of one or more measurements (e.g., critical dimension (CD) measurements) that would ordinarily be generated after destruction of a substrate, synthetic microscopy images, a prediction of a root cause (e.g., processing fault) of an anomaly of the product, and so on. These are a few representative examples of the uses of machine learning in association with manufacturing equipment, among many others.

[0019] In some embodiments, predictions may be made (e.g., using a machine learning model, a physics-based model, etc.) of metrology of a product. Metrology predictions may be made in view of target conditions in a processing chamber, in view of measurement of conditions proximate to a substrate, in view of in-situ (e.g., during processing) measurements of the product being processed, etc. In some embodiments, predicted metrology measurements may include a number of predictions of product dimensions, such as a prediction of thickness in the center of a substrate, etc.

[0020] In some embodiments, metrology data of a product may be measured. Performing metrology measurements may include obtaining one or more microscopy images of the product. Microscopy images may include images captured using optical techniques, electron-based techniques (e.g., scanning electron microscope (SEM) images, transmission electron microscope (TEM) images, etc.) or the like. In some embodiments, metrology of internal structures may be measured. Measuring internal structures of a product may include cutting a cross section of the product and taking an image of the interior structure. Advantages of performing microscopy of a cross section of a product include imaging interior structure, invisible under normal circumstances; providing the ability to make measurements (e.g., from microscopy images) of dimensions of a structure not measured or predicted otherwise; ensuring that predictive models maintain a threshold accuracy; etc. Metrology measurements (e.g., standalone metrology measurements, metrology measurements performed outside the

processing chamber, etc.) may be expensive and/or time consuming to perform. Metrology measurements (e.g., cross section microscopy) may disrupt or destroy the processed product.

[0021] In some embodiments, microscopy images may be used in training machine learning models. For example, dimensions measured by performing a cross sectional measurement (e.g., by SEM) may be provided to train a machine learning model as target output for predicting internal dimensions of a processed product. In some embodiments, a large volume of data is used to train a machine learning model. Hundreds, thousands, or more substrates may be used in training a machine learning model. Cost of performing comprehensive metrology, e.g., in time expended, materials expended, products destroyed and disposed of, energy and processing equipment used in production, etc., may be compounded by the large volume of data to be collected for training.

[0022] In some embodiments, microscopy images may vary (e.g., in contrast) due to differences in cross sectioning, exposure, etc., due to inconsistent measurement technique, different imaging technicians, or the like. Making measurements may be difficult using some images, further increasing the cost of generating sufficient data to train a machine learning model.

[0023] Methods and devices of the present disclosure may address one or more of these deficiencies of conventional solutions. In some embodiments, a realistic microscopy image (e.g., top-down image, cross sectional image, etc.) of a processed product is to be generated. The image may be utilized for measurement, visualization, input or training of a machine learning or other model, etc.

[0024] A synthetic microscopy image of a product may be generated using a machine learning model. In some embodiments, a large volume of historical image data may be available. For example, a large volume of historical data associated with related products, including related products of a different design, older generations of products, etc.; related manufacturing processes; related process recipes; etc., may be available for use in training a synthetic microscopy image generation machine learning model. In some embodiments, a generator model of a generative adversarial network (GAN) may be configured to generate synthetic data that matches distribution of the true data, e.g., that is statistically and structurally similar to a true microscopy image.

[0025] In some embodiments, the microscopy image generator may be configured to receive as input indications of dimensions of the product. In some embodiments, a machine learning model associated with a processing chamber (e.g., a machine learning model configured to receive as input sensor data during processing and generate as output one or

more indications of predicted metrology of a product) may produce output used by the synthetic image generator to generate a synthetic microscopy image. In some embodiments, an in-situ metrology measurement (e.g., spectral measurement of a substrate being processed) may be used as input to the synthetic image generator. In some embodiments, an integrated (e.g., a measurement taken while a substrate is still in vacuum but not being processed) or in-line (e.g., metrology measurement from equipment coupled to the processing equipment but outside the vacuum) measurement may be utilized by the synthetic microscopy image generator to generate a synthetic metrology image. In some embodiments, standalone metrology measurements (e.g., measurements made at a metrology facility, measurements less intrusive or destructive than the target image would be, such as measurements that do not destroy the substrate or include cross sectioning, etc.) may be utilized as input to the image generator.

[0026] In some embodiments, data used to train the generator model may be labeled with one or more attributes. Attributes may include labels identifying one or more features of the data. Attribute information may include data indicating a process recipe associated with a product, e.g., a sequence of recipe operations. Attribute information may include structural information of the product, e.g., may include indications of rules related to the order and/or placement of parts of the product being imaged. Attribute information may include data indicating product design. Attribute information may include target features of output data, e.g., may include a color scale, contrast value, and/or brightness value of the target synthetic image, etc. Attributes may include labels identifying a state of the manufacturing system, for example, a label of a fault present in the processing equipment, an indication of time since installation or maintenance of the manufacturing equipment, etc.

[0027] In some embodiments, the synthetic image generator may receive as input a cartoon structure, e.g., output by a cartoon generator model. The cartoon generator model may be configured to synthesize data indicative of measurements of a product (e.g., in-situ metrology, output of a predictive machine learning model, etc.) and additional product information (e.g., design of the product, type of device, order of structural layers, relationships between structure dimensions, etc.) to generate a cartoon picture of the product or device. The cartoon generator model may or may not be or include a trained machine learning model. The cartoon picture may be provided as input to the synthetic microscopy image generator. The generator may be configured to generate a realistic synthetic image which incorporates data from the cartoon, e.g., replicates structural information from the cartoon.

[0028] In some embodiments, generation of synthetic data may include the use of a generative adversarial network (GAN). A GAN is a type of unsupervised (e.g., training input is provided to the model without providing a target output during training operations) machine learning model. A basic GAN includes two parts: a generator and a discriminator. The generator produces synthetic data, e.g., synthetic microscopy image data. The discriminator is then provided with synthetic data and true data, e.g., data collected by collected a cross section SEM image of a product. The discriminator attempts to label data as true or synthetic, and the generator attempts to generate synthetic data that cannot be distinguished from true data by the discriminator. Once the generator achieves a target efficiency (e.g., reaches a threshold portion of output that the discriminator does not classify as synthetic), the generator may be used to produce synthetic data for use in other applications.

[0029] Aspects of the present disclosure result in technological advantages compared to conventional solutions. Technologies of the present disclosure enable generating accurate (e.g., similar enough to reality to draw conclusions) synthetic microscopy images of products, based on a number of measured or predicted metrology parameters and/or one or more design attributes of a manufactured device. In some embodiments, this approach allows for predictions of dimensions of a device that may generally be directly measured at great expense, e.g., using a standalone metrology facility, destroying the device to generate a cross-sectional image, etc. In some conventional systems, generating accurate (e.g., accurate above a threshold) predictions may include performing standalone metrology (e.g., destructive cross section imaging) on a large number of products. The large volume of data used to generate accurate predictions may be further exacerbated by changing chamber conditions (e.g., aging and drift, component replacement, maintenance, etc.), target rare events (e.g., fault or anomaly detection), etc. In conventional systems, a large number of processing runs may be performed to generate the data used to generate predictions. This may result in a large amount of wasted material, a large amount of chamber downtime, expended energy, etc. Metrology images (e.g., SEM microscopy images of a product) may have significant variance from image to image. Synthetic image data may be generated that is more consistent than measured data, e.g., by training the synthetic image generator using a selection of similar images, by configuring the generator to generate synthetic images with chosen values of contrast, brightness, or the like, etc.

[0030] In some embodiments, a machine learning model is to be trained using metrology images, e.g., to predict a fault present in a manufacturing or processing system based on a

microscopy image. Use of a synthetic microscopy image generator may enable quick and inexpensive generation of a large volume of synthetic microscopy data. The generator may be provided with attribute data to generate synthetic data with a target set of properties, which may be difficult to obtain otherwise. For example, the generator may be configured to generate image data associated with a product processed using equipment experiencing a fault. Recording image data indicative of a fault may include operating processing equipment under non-ideal conditions, which may increase cost, increase processing time, increase materials expended, increase energy expended, decrease component lifetime, or the like. Utilizing a generator to produce synthetic microscopy images may avoid these additional expenses.

[0031] In one aspect of the present disclosure, a method includes receiving data indicating a plurality of dimensions of a manufactured device. The method further includes providing the data to a trained machine learning model. The method further includes receiving, from the trained machine learning model, a synthetic microscopy image associated with the manufactured device, wherein the synthetic microscopy image is generated in view of the first data. The method further includes performing at least one of (i) outputting the synthetic microscopy image to a display or (ii) performing one or more operations on the synthetic microscopy image.

[0032] In another aspect of the disclosure, a method includes receiving a plurality of microscopy images of a plurality of manufactured devices. The method further includes receiving data indicating a plurality of dimensions of the plurality of manufactured device. The method further includes training a machine learning model, wherein training the machine learning model includes providing the first data to the machine learning model as training input. The training further includes providing the plurality of microscopy images to the machine learning model as target output.

[0033] In another aspect of the disclosure, a non-transitory machine-readable storage medium is disclosed. The storage medium stores instructions which, when executed, cause a processing device to perform operations. The operations include receiving data indicating a plurality of dimensions of a manufactured device. The operations further include providing the data to a trained machine learning model. The operations further include receiving, from the trained machine learning model, a synthetic microscopy image associated with the manufactured device. The synthetic microscopy image is generated in view of the first data. The operations further include performing at least one of (i) outputting the synthetic

microscopy image to a display or (ii) performing one or more operations on the synthetic microscopy image.

[0034] FIG. 1 is a block diagram illustrating an exemplary system 100 (exemplary system architecture), according to some embodiments. The system 100 includes a client device 120, manufacturing equipment 124, sensors 126, metrology equipment 128, predictive server 112, and data store 140. The predictive server 112 may be part of predictive system 110.

Predictive system 110 may further include server machines 170 and 180.

[0035] Sensors 126 may provide sensor data 142 associated with manufacturing equipment 124 (e.g., associated with producing, by manufacturing equipment 124, corresponding products, such as substrates). Sensor data 142 may be used to ascertain equipment health and/or product health (e.g., product quality). Manufacturing equipment 124 may produce products following a recipe or performing runs over a period of time. In some embodiments, sensor data 142 may include values of one or more of optical sensor data, spectral data, temperature (e.g., heater temperature), spacing (SP), pressure, High Frequency Radio Frequency (HFRF), radio frequency (RF) match voltage, RF match current, RF match capacitor position, voltage of Electrostatic Chuck (ESC), actuator position, electrical current, flow, power, voltage, etc. Sensor data 142 may include historical sensor data 144 and current sensor data 146. Current sensor data 146 may be associated with a product currently being processed, a product recently processed, a number of recently processed products, etc. Current sensor data 146 may be used as input to a trained machine learning model, e.g., to generate predictive data 168. Historical sensor data 144 may include data stored associated with previously produced products. Historical sensor data 144 may be used to train a machine learning model, e.g., model 190, synthetic data generator 174, etc. Historical sensor data 144 and/or current sensor data 146 may include attribute data, e.g., labels of manufacturing equipment ID or design, sensor ID, type, and/or location, label of a state of manufacturing equipment, such as a present fault, service lifetime, etc.

[0036] Sensor data 142 may be associated with or indicative of manufacturing parameters such as hardware parameters (e.g., hardware settings or installed components, e.g., size, type, etc.) of manufacturing equipment 124 or process parameters (e.g., heater settings, gas flow, etc.) of manufacturing equipment 124. Data associated with some hardware parameters and/or process parameters may, instead or additionally, be stored as manufacturing parameters 150, which may include historical manufacturing parameters (e.g., associated with historical processing runs) and current manufacturing parameters. Manufacturing parameters 150 may be indicative of input settings to the manufacturing device (e.g., heater power, gas

flow, etc.). Sensor data 142 and/or manufacturing parameters 150 may be provided while the manufacturing equipment 124 is performing manufacturing processes (e.g., equipment readings while processing products). Sensor data 142 may be different for each product (e.g., each substrate). Substrates may have property values (film thickness, film strain, etc.) measured by metrology equipment 128, e.g., measured at a standalone metrology facility. Metrology data 160 may be a component of data store 140. Metrology data 160 may include historical metrology data 164 (e.g., metrology data associated with previously processed products).

[0037] In some embodiments, metrology data 160 may be provided without use of a standalone metrology facility, e.g., in-situ metrology data (e.g., metrology or a proxy for metrology collected during processing), integrated metrology data (e.g., metrology or a proxy for metrology collected while a product is within a chamber or under vacuum, but not during processing operations), inline metrology data (e.g., data collected after a substrate is removed from vacuum), etc. Metrology data 160 may include current metrology data 166 (e.g., metrology data associated with a product currently or recently processed).

[0038] In some embodiments, sensor data 142, metrology data 160, or manufacturing parameters 150 may be processed (e.g., by the client device 120 and/or by the predictive server 112). Processing of the sensor data 142 may include generating features. In some embodiments, the features are a pattern in the sensor data 142, metrology data 160, and/or manufacturing parameters 150 (e.g., slope, width, height, peak, etc.) or a combination of values from the sensor data 142, metrology data, and/or manufacturing parameters (e.g., power derived from voltage and current, etc.). Sensor data 142 may include features and the features may be used by predictive component 114 for performing signal processing and/or for obtaining predictive data 168 for performance of a corrective action.

[0039] Each instance (e.g., set) of sensor data 142 may correspond to a product (e.g., a substrate), a set of manufacturing equipment, a type of substrate produced by manufacturing equipment, or the like. Each instance of metrology data 160 and manufacturing parameters 150 may likewise correspond to a product, a set of manufacturing equipment, a type of substrate produced by manufacturing equipment, or the like. The data store may further store information associating sets of different data types, e.g. information indicative that a set of sensor data, a set of metrology data, and a set of manufacturing parameters are all associated with the same product, manufacturing equipment, type of substrate, etc.

[0040] In some embodiments, a processing device (e.g., via a machine learning model) may be used to generate synthetic data 162. Synthetic data may be processed in any of the

ways described above in connection with other types of data, e.g., generating features, combining values, linking data from a particular recipe, chamber, or substrate, etc. Synthetic data 162 may share features with some metrology data 160, e.g., may include image data, may resemble microscopy images included in metrology data 160 (e.g., SEM and/or TEM images), etc.

[0041] In some embodiments, predictive system 110 may generate predictive data 168 using supervised machine learning (e.g., predictive data 168 includes output from a machine learning model that was trained using labeled data, such as sensor data labeled with metrology data (e.g., which may include synthetic microscopy images generated according to embodiments herein, etc.). In some embodiments, predictive system 110 may generate predictive data 168 using unsupervised machine learning (e.g., predictive data 168 includes output from a machine learning model that was trained using unlabeled data, output may include clustering results, principle component analysis, anomaly detection, etc.). In some embodiments, predictive system 110 may generate predictive data 168 using semi-supervised learning (e.g., training data may include a mix of labeled and unlabeled data, etc.).

[0042] Client device 120, manufacturing equipment 124, sensors 126, metrology equipment 128, predictive server 112, data store 140, server machine 170, and server machine 180 may be coupled to each other via network 130 for generating predictive data 168 to perform corrective actions. In some embodiments, network 130 may provide access to cloud-based services. Operations performed by client device 120, predictive system 110, data store 140, etc., may be performed by virtual cloud-based devices.

[0043] In some embodiments, network 130 is a public network that provides client device 120 with access to the predictive server 112, data store 140, and other publicly available computing devices. In some embodiments, network 130 is a private network that provides client device 120 access to manufacturing equipment 124, sensors 126, metrology equipment 128, data store 140, and other privately available computing devices. Network 130 may include one or more Wide Area Networks (WANs), Local Area Networks (LANs), wired networks (e.g., Ethernet network), wireless networks (e.g., an 802.11 network or a Wi-Fi network), cellular networks (e.g., a Long Term Evolution (LTE) network), routers, hubs, switches, server computers, cloud computing networks, and/or a combination thereof.

[0044] Client device 120 may include computing devices such as Personal Computers (PCs), laptops, mobile phones, smart phones, tablet computers, netbook computers, network connected televisions (“smart TV”), network-connected media players (e.g., Blu-ray player), a set-top-box, Over-the-Top (OTT) streaming devices, operator boxes, etc. Client device 120

may include a corrective action component 122. Corrective action component 122 may receive user input (e.g., via a Graphical User Interface (GUI) displayed via the client device 120) of an indication associated with manufacturing equipment 124. In some embodiments, corrective action component 122 transmits the indication to the predictive system 110, receives output (e.g., predictive data 168) from the predictive system 110, determines a corrective action based on the output, and causes the corrective action to be implemented. In some embodiments, corrective action component 122 obtains sensor data 142 (e.g., current sensor data 146) associated with manufacturing equipment 124 (e.g., from data store 140, etc.) and provides sensor data 142 (e.g., current sensor data 146) associated with the manufacturing equipment 124 to predictive system 110.

[0045] In some embodiments, corrective action component 122 may retrieve current metrology data 166 (e.g., predictive or proxy metrology measurements of a product in processing) and provide it to synthetic data generator 174. Synthetic data generator 174 may produce as output a predictive synthetic microscopy image of the product associated with current metrology data 166. Corrective action component 122 may store the synthetic image data in data store 140. In some embodiments, corrective action component 122 stores data to be used as input to a machine learning or other model (e.g., current sensor data 146 to be provided to model 190, current metrology data 166 to be provided to synthetic data generator 174, etc.) in data store 140 and a component of predictive system 110 (e.g., predictive server 112, server machine 170) retrieves sensor data 142 from data store 140. In some embodiments, predictive server 112 may store output (e.g., predictive data 168) of the trained model(s) 190 in data store 140 and client device 120 may retrieve the output from data store 140.

[0046] In some embodiments, corrective action component 122 receives an indication of a corrective action from the predictive system 110 and causes the corrective action to be implemented. Each client device 120 may include an operating system that allows users to one or more of generate, view, or edit data (e.g., indication associated with manufacturing equipment 124, corrective actions associated with manufacturing equipment 124, etc.).

[0047] In some embodiments, metrology data 160 (e.g., historical metrology data 164) corresponds to historical property data of products (e.g., products processed using manufacturing parameters associated with historical sensor data 144 and historical manufacturing parameters of manufacturing parameters 150) and predictive data 168 is associated with predicted property data (e.g., of products to be produced or that have been produced in conditions recorded by current sensor data 146 and/or current manufacturing

parameters). In some embodiments, predictive data 168 is or includes predicted metrology data (e.g., virtual metrology data, virtual synthetic microscopy images) of the products to be produced or that have been produced according to conditions recorded as current sensor data 146, current measurement data, current metrology data and/or current manufacturing parameters. In some embodiments, predictive data 168 is or includes an indication of any abnormalities (e.g., abnormal products, abnormal components, abnormal manufacturing equipment 124, abnormal energy usage, etc.) and optionally one or more causes of the abnormalities. In some embodiments, predictive data 168 is an indication of change over time or drift in some component of manufacturing equipment 124, sensors 126, metrology equipment 128, and the like. In some embodiments, predictive data 168 is an indication of an end of life of a component of manufacturing equipment 124, sensors 126, metrology equipment 128, or the like. In some embodiments, predictive data 168 is an indication of progress of a processing operation being performed, e.g., to be used for process control.

[0048] Performing manufacturing processes that result in defective products can be costly in time, energy, products, components, manufacturing equipment 124, the cost of identifying the defects and discarding the defective product, etc. By inputting sensor data 142 (e.g., manufacturing parameters that are being used or are to be used to manufacture a product) into predictive system 110, receiving output of predictive data 168, and performing a corrective action based on the predictive data 168, system 100 can have the technical advantage of avoiding the cost of producing, identifying, and discarding defective products. By supplying some predicted metrology measurements to synthetic data generator 174 and receiving as output a synthetic microscopy image, products which are not predicted to meet performance thresholds may be identified and production halted, corrective actions performed, alerts sent to users, recipes updated, etc.

[0049] Performing manufacturing processes that result in failure of the components of the manufacturing equipment 124 can be costly in downtime, damage to products, damage to equipment, express ordering replacement components, etc. By inputting sensor data 142 (e.g., manufacturing parameters that are being used or are to be used to manufacture a product), metrology data, measurement data, etc., receiving output of predictive data 168, and performing corrective action (e.g., predicted operational maintenance, such as replacement, processing, cleaning, etc. of components) based on the predictive data 168, system 100 can have the technical advantage of avoiding the cost of one or more of unexpected component failure, unscheduled downtime, productivity loss, unexpected equipment failure, product scrap, or the like. Monitoring the performance over time of components, e.g. manufacturing

equipment 124, sensors 126, metrology equipment 128, and the like, may provide indications of degrading components.

[0050] Manufacturing parameters may be suboptimal for producing product which may have costly results of increased resource (e.g., energy, coolant, gases, etc.) consumption, increased amount of time to produce the products, increased component failure, increased amounts of defective products, etc. By inputting indications of metrology into synthetic data generator 174, receiving an output of synthetic data 162, and performing (e.g., based on synthetic data 162) a corrective action of updating manufacturing parameters (e.g., setting optimal manufacturing parameters), system 100 can have the technical advantage of using optimal manufacturing parameters (e.g., hardware parameters, process parameters, optimal design) to avoid costly results of suboptimal manufacturing parameters.

[0051] Corrective actions may be associated with one or more of Computational Process Control (CPC), Statistical Process Control (SPC) (e.g., SPC on electronic components to determine process in control, SPC to predict useful lifespan of components, SPC to compare to a graph of 3-sigma, etc.), Advanced Process Control (APC), model-based process control, preventative operative maintenance, design optimization, updating of manufacturing parameters, updating manufacturing recipes, feedback control, machine learning modification, or the like.

[0052] In some embodiments, the corrective action includes providing an alert (e.g., an alarm to stop or not perform the manufacturing process if the predictive data 168 indicates a predicted abnormality, such as an abnormality of the product, a component, or manufacturing equipment 124). In some embodiments, a machine learning model is trained to monitor the progress of a processing run (e.g., monitor in-situ sensor data to predict if a manufacturing process has reached completion). In some embodiments, the machine learning model may send instructions to end a processing run when the model determines that the process is complete. In some embodiments, the corrective action includes providing feedback control (e.g., modifying a manufacturing parameter responsive to the predictive data 168 indicating a predicted abnormality). In some embodiments, performance of the corrective action includes causing updates to one or more manufacturing parameters. In some embodiments performance of a corrective action may include retraining a machine learning model associated with manufacturing equipment 124. In some embodiments, performance of a corrective action may include training a new machine learning model associated with manufacturing equipment 124.

[0053] Manufacturing parameters 150 may include hardware parameters (e.g., information indicative of which components are installed in manufacturing equipment 124, indicative of component replacements, indicative of component age, indicative of software version or updates, etc.) and/or process parameters (e.g., temperature, pressure, flow, rate, electrical current, voltage, gas flow, lift speed, etc.). In some embodiments, the corrective action includes causing preventative operative maintenance (e.g., replace, process, clean, etc. components of the manufacturing equipment 124). In some embodiments, the corrective action includes causing design optimization (e.g., updating manufacturing parameters, manufacturing processes, manufacturing equipment 124, etc. for an optimized product). In some embodiments, the corrective action includes updating a recipe (e.g., altering the timing of manufacturing subsystems entering an idle or active mode, altering set points of various property values, etc.).

[0054] Predictive server 112, server machine 170, and server machine 180 may each include one or more computing devices such as a rackmount server, a router computer, a server computer, a personal computer, a mainframe computer, a laptop computer, a tablet computer, a desktop computer, Graphics Processing Unit (GPU), accelerator Application-Specific Integrated Circuit (ASIC) (e.g., Tensor Processing Unit (TPU)), etc. Operations of predictive server 112, server machine 170, server machine 180, data store 140, etc., may be performed by a cloud computing service, cloud data storage service, etc.

[0055] Predictive server 112 may include a predictive component 114. In some embodiments, the predictive component 114 may receive current sensor data 146, and/or current manufacturing parameters (e.g., receive from the client device 120, retrieve from the data store 140) and generate output (e.g., predictive data 168) for performing corrective action associated with the manufacturing equipment 124 based on the current data. In some embodiments, predictive data 168 may include one or more predicted dimension measurements of a processed product. In some embodiments, predictive data 168 may be provided to synthetic data generator 174 for generation of synthetic microscopy image data, e.g., synthetic data 162. In some embodiments, predictive component 114 may use one or more trained machine learning models 190 to determine the output for performing the corrective action based on current data.

[0056] Manufacturing equipment 124 may be associated with one or more machine learning models, e.g., model 190. Machine learning models associated with manufacturing equipment 124 may perform many tasks, including process control, classification, performance predictions, etc. Model 190 may be trained using data associated with

manufacturing equipment 124 or products processed by manufacturing equipment 124, e.g., sensor data 142 (e.g., collected by sensors 126), manufacturing parameters 150 (e.g., associated with process control of manufacturing equipment 124), metrology data 160 (e.g., generated by metrology equipment 128), etc.

[0057] One type of machine learning model that may be used to perform some or all of the above tasks is an artificial neural network, such as a deep neural network. Artificial neural networks generally include a feature representation component with a classifier or regression layers that map features to a desired output space. A convolutional neural network (CNN), for example, hosts multiple layers of convolutional filters. Pooling is performed, and non-linearities may be addressed, at lower layers, on top of which a multi-layer perceptron is commonly appended, mapping top layer features extracted by the convolutional layers to decisions (e.g. classification outputs).

[0058] A recurrent neural network (RNN) is another type of machine learning model. A recurrent neural network model is designed to interpret a series of inputs where inputs are intrinsically related to one another, e.g., time trace data, sequential data, etc. Output of a perceptron of an RNN is fed back into the perceptron as input, to generate the next output.

[0059] Deep learning is a class of machine learning algorithms that use a cascade of multiple layers of nonlinear processing units for feature extraction and transformation. Each successive layer uses the output from the previous layer as input. Deep neural networks may learn in a supervised (e.g., classification) and/or unsupervised (e.g., pattern analysis) manner. Deep neural networks include a hierarchy of layers, where the different layers learn different levels of representations that correspond to different levels of abstraction. In deep learning, each level learns to transform its input data into a slightly more abstract and composite representation. In an image recognition application, for example, the raw input may be a matrix of pixels; the first representational layer may abstract the pixels and encode edges; the second layer may compose and encode arrangements of edges; the third layer may encode higher level shapes (e.g., teeth, lips, gums, etc.); and the fourth layer may recognize a scanning role. Notably, a deep learning process can learn which features to optimally place in which level on its own. The "deep" in "deep learning" refers to the number of layers through which the data is transformed. More precisely, deep learning systems have a substantial credit assignment path (CAP) depth. The CAP is the chain of transformations from input to output. CAPs describe potentially causal connections between input and output. For a feedforward neural network, the depth of the CAPs may be that of the network and may be the number of

hidden layers plus one. For recurrent neural networks, in which a signal may propagate through a layer more than once, the CAP depth is potentially unlimited.

[0060] In some embodiments, predictive component 114 and/or model 190 includes a generator of a generative adversarial network (GAN) that has been trained to generate synthetic microscopy images. A machine learning model may be trained by including the target model in a generative adversarial network (GAN). A GAN puts two (or more) machine learning models in opposition (e.g., adversarial arrangement) to facilitate training of the models. A simple GAN includes a generator and a discriminator. The generator is configured to generate synthetic data resembling data from a set of true data. The discriminator is configured to classify output from the generator as true data or synthetic data. The model weights and biases are adjusted to improve the generator's data generation and improve the discriminator's classification. A GAN may be configured to convert images from one space to another, e.g., replace some property of an input image with another. An image-to-image (e.g., pix2pix) GAN may be configured to convert a primitive drawing or cartoon into a realistic image in embodiments. In some embodiments, the discriminator of an image-to-image GAN may be provided with an original (e.g., true) image and/or the synthetic image produced by the generator and classify which of the two is true and which synthetic.

[0061] In some embodiments, predictive component 114 receives current sensor data 146, current metrology data 166 and/or current manufacturing parameters 154, performs signal processing to break down the current data into sets of current data, provides the sets of current data as input to a trained model 190, and obtains outputs indicative of predictive data 168 from the trained model 190. In some embodiments, predictive component 114 receives metrology data (e.g., predicted metrology data based on sensor data) of a substrate and provides the metrology data to trained model 190. For example, current sensor data 146 may include sensor data indicative of metrology (e.g., geometry) of a substrate. Model 190 may be configured to accept data indicative of substrate metrology and generate as output a predictive synthetic microscopy image. In some embodiments, predictive data is indicative of metrology data (e.g., prediction of substrate quality). In some embodiments, predictive data is indicative of component health. In some embodiments, predictive data is indicative of processing progress (e.g., utilized to end a processing operation).

[0062] In some embodiments, the various models discussed in connection with model 190 (e.g., supervised machine learning model, unsupervised machine learning model, etc.) may be combined in one model (e.g., an ensemble model), or may be separate models.

[0063] Data may be passed back and forth between several distinct models included in model 190, synthetic data generator 174, and predictive component 114. In some embodiments, some or all of these operations may instead be performed by a different device, e.g., client device 120, server machine 170, server machine 180, etc. It will be understood by one of ordinary skill in the art that variations in data flow, which components perform which processes, which models are provided with which data, and the like are within the scope of this disclosure.

[0064] Data store 140 may be a memory (e.g., random access memory), a drive (e.g., a hard drive, a flash drive), a database system, a cloud-accessible memory system, or another type of component or device capable of storing data. Data store 140 may include multiple storage components (e.g., multiple drives or multiple databases) that may span multiple computing devices (e.g., multiple server computers). The data store 140 may store sensor data 142, manufacturing parameters 150, metrology data 160, synthetic data 162, and predictive data 168.

[0065] Sensor data 142 may include historical sensor data 144 and current sensor data 146. Sensor data may include sensor data time traces over the duration of manufacturing processes, associations of data with physical sensors, pre-processed data, such as averages and composite data, and data indicative of sensor performance over time (i.e., many manufacturing processes). Manufacturing parameters 150 and metrology data 160 may contain similar features, e.g., historical metrology data 164 and current metrology data 166. Historical sensor data 144, historical metrology data 166, and historical manufacturing parameters may be historical data (e.g., at least a portion of these data may be used for training model 190). Current sensor data 146, current metrology data 166, may be current data (e.g., at least a portion to be input into learning model 190, subsequent to the historical data) for which predictive data 168 is to be generated (e.g., for performing corrective actions). Synthetic data 162 may include synthetic images generated by synthetic data generator 174, e.g., synthetic data that resemble scanning electron microscope (SEM) images, transmission electron microscope (TEM) images, or the like.

[0066] In some embodiments, predictive system 110 further includes server machine 170 and server machine 180. Server machine 170 includes a data set generator 172 that is capable of generating data sets (e.g., a set of data inputs and a set of target outputs) to train, validate, and/or test model(s) 190, including one or more machine learning models. Some operations of data set generator 172 are described in detail below with respect to FIGS. 2A-B and 4A. In some embodiments, data set generator 172 may partition the historical data (e.g., historical

sensor data 144, historical manufacturing parameters, historical metrology data 164) into a training set (e.g., sixty percent of the historical data), a validating set (e.g., twenty percent of the historical data), and a testing set (e.g., twenty percent of the historical data).

[0067] In some embodiments, predictive system 110 (e.g., via predictive component 114) generates multiple sets of features. For example a first set of features may correspond to a first set of types of sensor data (e.g., from a first set of sensors, first combination of values from first set of sensors, first patterns in the values from the first set of sensors) that correspond to each of the data sets (e.g., training set, validation set, and testing set) and a second set of features may correspond to a second set of types of sensor data (e.g., from a second set of sensors different from the first set of sensors, second combination of values different from the first combination, second patterns different from the first patterns) that correspond to each of the data sets.

[0068] Server machine 170 may include synthetic data generator 174. Synthetic data generator 174 may include one or more trained machine learning models, physics-based models, rule-based models, or the like. In one embodiment, synthetic data generator 174 is or includes a generator of a GAN, such as a generator of an image to image GAN. Synthetic data generator 174 may be trained to generate synthetic microscopy images from input data. In embodiments, the input data is or includes a simple line drawing or cartoon drawing of a cross-sectional side view of a device or structure. Synthetic data generator 174 may be trained using metrology data 160, e.g., collected by metrology equipment 128. Synthetic data generator 174 may be configured to generate synthetic data, e.g., synthetic microscopy image data. Synthetic data 162 may resemble historical metrology data 164. Synthetic data 162 may be used to train machine learning model 190, e.g., for generation of predictive data 168 for performance of a corrective action. Data set generator 172 may combine metrology data 160 and synthetic data 162 to generate training, testing, validating, etc., data sets.

[0069] In some embodiments, synthetic data generator 174 may be configured to generate synthetic microscopy images of manufactured products. Synthetic data generator 174 may be provided with true microscopy images (e.g., images of manufactured devices collected by a microscopy system, such as an SEM or TEM system) during training operations and configured to generate synthetic images resembling the true images. In some embodiments, synthetic data generator 174 may be provided with indications of dimensions of a substrate in training. For example, output of an in-situ metrology system may be provided during training operations to synthetic data generator 174. Synthetic data generator 174 may be configured to accept one or more indications of metrology (e.g., a list of measurements from a metrology

system, a list of predicted measurements from a model configured to predict substrate dimensions, etc.) and generate as output one or more synthetic microscopy images. In some embodiments, synthetic data generator 174 may be provided indications of metrology of a manufactured product in the form of a cartoon image of the product. In some embodiments, synthetic data generator 174 may include a cartoon generator.

[0070] In some embodiments, output from synthetic data generator 174 may be utilized for performance analysis (e.g., predicted substrate performance, substrate processing system performance analysis, etc.). In some embodiments, output from synthetic data generator 174 may be utilized to select a substrate for further investigation, e.g., may be used to flag a substrate that may be faulty for further metrology. In some embodiments, output from synthetic data generator 174 may be provided to another model, e.g., another machine learning model. The second model may be configured to accept one or more metrology images associated with a substrate. The second model may be configured to determine faults, estimate performance, recommend corrective actions, etc., based on a microscopy image (e.g., a synthetic microscopy image generated by synthetic data generator 174).

[0071] In some embodiments, machine learning model 190 is provided historical data as training data. In some embodiments, machine learning model 190 is provided synthetic data 162 as training data. The historical and/or synthetic sensor data may be or include microscopy image data in some embodiments. The type of data provided will vary depending on the intended use of the machine learning model. For example, a machine learning model may be trained by providing the model with historical sensor data 144 as training input and corresponding metrology data 160 as target output. In some embodiments, a large volume of data is used to train model 190, e.g., sensor and metrology data of hundreds of substrates may be used. In some embodiments, a fairly small volume of data is available to train model 190, e.g., model 190 is to be trained to recognize a rare event such as equipment failure, model 190 is to be trained to generate predictions of a newly seasoned or maintained chamber, etc. Synthetic data 162 may be generated by synthetic data generator 174 to augment available true data (e.g., data generated by metrology equipment 128) in training model 190.

[0072] Server machine 180 includes a training engine 182, a validation engine 184, selection engine 185, and/or a testing engine 186. An engine (e.g., training engine 182, a validation engine 184, selection engine 185, and a testing engine 186) may refer to hardware (e.g., circuitry, dedicated logic, programmable logic, microcode, processing device, etc.), software (such as instructions run on a processing device, a general purpose computer system, or a dedicated machine), firmware, microcode, or a combination thereof. The training

engine 182 may be capable of training a model 190 and/or synthetic data generator 174 using one or more sets of features associated with the training set from data set generator 172. The training engine 182 may generate multiple trained models 190, where each trained model 190 corresponds to a distinct set of features of the training set (e.g., sensor data from a distinct set of sensors). For example, a first trained model may have been trained using all features (e.g., X1-X5), a second trained model may have been trained using a first subset of the features (e.g., X1, X2, X4), and a third trained model may have been trained using a second subset of the features (e.g., X1, X3, X4, and X5) that may partially overlap the first subset of features. Data set generator 172 may receive the output of a trained model (e.g., synthetic data 162 from synthetic data generator 174), collect that data into training, validation, and testing data sets, and use the data sets to train a second model (e.g., a machine learning model configured to output predictive data, corrective actions, etc.).

[0073] Validation engine 184 may be capable of validating a trained model 190 using a corresponding set of features of the validation set from data set generator 172. For example, a first trained machine learning model 190 that was trained using a first set of features of the training set may be validated using the first set of features of the validation set. The validation engine 184 may determine an accuracy of each of the trained models 190 based on the corresponding sets of features of the validation set. Validation engine 184 may discard trained models 190 that have an accuracy that does not meet a threshold accuracy. In some embodiments, selection engine 185 may be capable of selecting one or more trained models 190 that have an accuracy that meets a threshold accuracy. In some embodiments, selection engine 185 may be capable of selecting the trained model 190 that has the highest accuracy of the trained models 190.

[0074] Testing engine 186 may be capable of testing a trained model 190 using a corresponding set of features of a testing set from data set generator 172. For example, a first trained machine learning model 190 that was trained using a first set of features of the training set may be tested using the first set of features of the testing set. Testing engine 186 may determine a trained model 190 that has the highest accuracy of all of the trained models based on the testing sets.

[0075] In the case of a machine learning model, model 190 may refer to the model artifact that is created by training engine 182 using a training set that includes data inputs and corresponding target outputs (correct answers for respective training inputs). In embodiments, the training set includes synthetic microscopy images generated by synthetic data generator 174. Patterns in the data sets can be found that map the data input to the target output (the

correct answer), and machine learning model 190 is provided mappings that capture these patterns. The machine learning model 190 may use one or more of Support Vector Machine (SVM), Radial Basis Function (RBF), clustering, supervised machine learning, semi-supervised machine learning, unsupervised machine learning, k-Nearest Neighbor algorithm (k-NN), linear regression, random forest, neural network (e.g., artificial neural network, recurrent neural network), etc. Synthetic data generator 174 may include one or more machine learning models, which may include one or more of the same types of models (e.g., artificial neural network).

[0076] In some embodiments, one or more machine learning models 190 may be trained using historical data (e.g., historical sensor data 144). In some embodiments, models 190 may have been trained using synthetic data 162, or a combination of historical data and synthetic data.

[0077] In some embodiments, synthetic data generator 174 may be trained using historical data. For example, synthetic data generator 174 may be trained using historical metrology data 164 to generate synthetic data 162. In some embodiments, synthetic data generator 174 may include a generative adversarial network (GAN). A GAN includes at least a generator and a discriminator. The generator attempts to generate data (e.g., time trace sensor data) similar to input data (e.g., true sensor data). The discriminator attempts to distinguish true data from synthetic data. Training the GAN includes the generator becoming more adept at generating data that resembles true sensor data, and the discriminator becoming more adept at distinguishing true from synthetic data. A trained GAN includes a generator that is configured to generate synthetic data that includes many features of the true data used to train it. In some embodiments, the input data may be labelled with one or more attributes, such as information about the tool, sensor, product, or product design associated with the input data. In some embodiments, the generator may be configured to produce synthetic data with a certain set of attributes, e.g., synthetic data associated with a target processing operation, target processing equipment fault, target metrology configuration (e.g., contrast, cross section or top-down image, brightness, etc.), or the like.

[0078] Generating and utilizing synthetic data 162 has significant technical advantages over other methods. In some embodiments, a measurement of one or more dimensions of a device is to be generated. Some measurements may be made with inexpensive, non-destructive methods. For example, in-situ reflective spectral data may correlate with an etch depth, integrated or inline metrology may similarly provide one or more dimensions of the produced device. In some embodiments, a target dimension measurement is not easily

obtained, e.g., a measurement of a dimension of an internal structure of the product or device. Directly measuring a target dimension may be costly in terms of time, e.g., be measurement may be performed at a standalone metrology facility, or material, e.g., may be destructive to the product. Measurements difficult to obtain via inexpensive conventional methods may be obtained by making measurements of synthetic data 162, e.g., by calculating measurements of the product from one or more synthetic microscopy images. The synthetic data 162 generated by the synthetic data generator 174 may have a high degree of accuracy. Accordingly, synthetic data generator 174 may generate synthetic data that provides information on internal structures of a substrate that are otherwise obtainable by destructive means.

[0079] Synthetic data 162 may additionally offer technical advantages when used to train further models, such as model 190. In some embodiments, a large amount of data (e.g., data from hundreds of substrates) may be used to train a machine learning model, a physics-based model, etc. It may be expensive to generate such a volume of data, e.g., in raw materials expended, process gasses, energy, time, equipment wear, etc. Synthetic data generator 174 may be used to quickly and cheaply generate a large volume of image data that may be used to train a model.

[0080] In some embodiments, true microscopy images may vary in unpredictable or detrimental ways. For example, different images may have different characteristics, such as contrast, brightness, clarity, etc. This may be due to operator error, microscopy procedure, etc. Synthetic data 162 may be tuned to exhibit desired characteristics. In some embodiments, training data may be selected (e.g., by a user, by an algorithm, etc.) to train the synthetic data generator 174 that exhibits the desired characteristics. In some embodiments, the generator may be provided with attribute data describing the characteristics of the image, and may be configured to generate images according to a target set of attributes and/or characteristics.

[0081] Predictive component 114 may provide current data to model 190 and may run model 190 on the input to obtain one or more outputs. For example, predictive component 114 may provide current sensor data 146 to model 190 and may run model 190 on the input to obtain one or more outputs. Predictive component 114 may be capable of determining (e.g., extracting) predictive data 168 from the output of model 190. Predictive component 114 may determine (e.g., extract) confidence data from the output that indicates a level of confidence that predictive data 168 is an accurate predictor of a process associated with the input data for products produced or to be produced using the manufacturing equipment 124 at the current sensor data 146 and/or current manufacturing parameters. Predictive component

114 or corrective action component 122 may use the confidence data to decide whether to cause a corrective action associated with the manufacturing equipment 124 based on predictive data 168.

[0082] The confidence data may include or indicate a level of confidence that the predictive data 168 is an accurate prediction for products or components associated with at least a portion of the input data. In one example, the level of confidence is a real number between 0 and 1 inclusive, where 0 indicates no confidence that the predictive data 168 is an accurate prediction for products processed according to input data or component health of components of manufacturing equipment 124 and 1 indicates absolute confidence that the predictive data 168 accurately predicts properties of products processed according to input data or component health of components of manufacturing equipment 124. Responsive to the confidence data indicating a level of confidence below a threshold level for a predetermined number of instances (e.g., percentage of instances, frequency of instances, total number of instances, etc.) predictive component 114 may cause trained model 190 to be re-trained (e.g., based on current sensor data 146, current manufacturing parameters, etc.). In some embodiments, retraining may include generating one or more data sets (e.g., via data set generator 172) utilizing historical data and/or synthetic data.

[0083] For purpose of illustration, rather than limitation, aspects of the disclosure describe the training of one or more machine learning models 190 using historical data (e.g., historical sensor data 144, historical manufacturing parameters) and synthetic data 162 and inputting current data (e.g., current sensor data 146, current manufacturing parameters, and current metrology data) into the one or more trained machine learning models to determine predictive data 168. In other embodiments, a heuristic model, physics-based model, or rule-based model is used to determine predictive data 168 (e.g., without using a trained machine learning model). In some embodiments, such models may be trained using historical and/or synthetic data. In some embodiments, these models may be retrained utilizing a combination of true historical data and synthetic data. Predictive component 114 may monitor historical sensor data 144, historical manufacturing parameters, and metrology data 160. Any of the information described with respect to data inputs 210A-B of FIGS. 2A-B may be monitored or otherwise used in the heuristic, physics-based, or rule-based model.

[0084] In some embodiments, the functions of client device 120, predictive server 112, server machine 170, and server machine 180 may be provided by a fewer number of machines. For example, in some embodiments server machines 170 and 180 may be integrated into a single machine, while in some other embodiments, server machine 170,

server machine 180, and predictive server 112 may be integrated into a single machine. In some embodiments, client device 120 and predictive server 112 may be integrated into a single machine. In some embodiments, functions of client device 120, predictive server 112, server machine 170, server machine 180, and data store 140 may be performed by a cloud-based service.

[0085] In general, functions described in one embodiment as being performed by client device 120, predictive server 112, server machine 170, and server machine 180 can also be performed on predictive server 112 in other embodiments, if appropriate. In addition, the functionality attributed to a particular component can be performed by different or multiple components operating together. For example, in some embodiments, the predictive server 112 may determine the corrective action based on the predictive data 168. In another example, client device 120 may determine the predictive data 168 based on output from the trained machine learning model.

[0086] In addition, the functions of a particular component can be performed by different or multiple components operating together. One or more of the predictive server 112, server machine 170, or server machine 180 may be accessed as a service provided to other systems or devices through appropriate application programming interfaces (API).

[0087] In embodiments, a “user” may be represented as a single individual. However, other embodiments of the disclosure encompass a “user” being an entity controlled by a plurality of users and/or an automated source. For example, a set of individual users federated as a group of administrators may be considered a “user.”

[0088] Embodiments of the disclosure may be applied to data quality evaluation, feature enhancement, model evaluation, Virtual Metrology (VM), Predictive Maintenance (PdM), limit optimization, process control, or the like.

[0089] FIGS. 2A-B depict block diagrams of example data set generators 272A-B (e.g., data set generator 172 of FIG. 1) to create data sets for training, testing, validating, etc. a model (e.g., model 190 of FIG. 1), according to some embodiments. Each data set generator 272 may be part of server machine 170 of FIG. 1. In some embodiments, several machine learning models associated with manufacturing equipment 124 may be trained, used, and maintained (e.g., within a manufacturing facility). Each machine learning model may be associated with one data set generators 272, multiple machine learning models may share a data set generator 272, etc.

[0090] FIG. 2A depicts a system 200A including data set generator 272A for creating data sets for one or more supervised models (e.g., synthetic data generator 174 of FIG. 1).

Data set generator 272A may create data sets (e.g., data input 210A, target output 220A) using historical data and/or design rule data. In some embodiments, a data set generator similar to data set generator 272A may be utilized to train an unsupervised machine learning model, e.g., target output 220A may not be generated by data set generator 272A.

[0091] Data set generator 272A may generate data sets to train, test, and validate a model. In some embodiments, data set generator 272A may generate data sets for a machine learning model. In some embodiments, data set generator 272A may generate data sets for training, testing, and/or validating a generator model configured to generate synthetic microscopy image data. The machine learning model is provided with set of historical metrology data 264A and/or set of design rule data 265A as data input 210A. The machine learning model may be configured to accept metrology and design rule data as input data and generate synthetic microscopy image data as output.

[0092] In some embodiments, data set generator 272A may be configured to generate data sets for training, testing, validating, etc., a generative adversarial network (GAN). In some embodiments, data set generator 272A may be used to generate data sets for an image-to-image (e.g., pix-2-pix) GAN. In some embodiments, design rule data may be provided to train the machine learning model. In some embodiments, metrology data and design rule data may be provided to another model, which generates data synthesizing information from both the metrology and design rule data to provide to the machine learning model. In some embodiments, the synthesis model may generate a predictive cartoon image of a manufactured product, e.g., incorporating known metrology measurements and various rules of design. In reference to FIG. 2A, it will be assumed that the data set generator supplies both metrology data and design rule data to the model, e.g., the model may be considered an ensemble model incorporating a cartoon generator and an image-to-image GAN.

[0093] Data set generator 272A may be used to generate data for any type of machine learning model that takes as input metrology and/or design rule data. Data set generator 272A may be used to generate data for a machine learning model that generates predicted metrology data of a substrate. Data set generator 272A may be used to generate data for a machine learning model configured to provide process control instructions. Data set generator 272A may be used to generate data for a machine learning model configured to identify a product anomaly and/or processing equipment fault.

[0094] In some embodiments, data set generator 272A generates a data set (e.g., training set, validating set, testing set) that includes one or more data inputs 210A (e.g., training input, validating input, testing input). Data inputs 210A may be provided to training engine 182,

validating engine 184, or testing engine 186. The data set may be used to train, validate, or test the model (e.g., synthetic data generator 174 of FIG. 1).

[0095] In some embodiments, data input 210A may include one or more sets of data. As an example, system 200A may produce sets of sensor data that may include one or more of sensor data from one or more types of sensors, combinations of sensor data from one or more types of sensors, patterns from sensor data from one or more types of sensors, and/or synthetic versions thereof.

[0096] In some embodiments, data input 210A may include one or more sets of data. As an example, system 200A may produce sets of historical metrology data that may include one or more of metrology data of a group of dimensions of a device (e.g., include height and width of the device but not optical data or surface roughness, etc.), metrology data derived from one or more types of sensors, combination of metrology data derived from one or more types of sensors, patterns from metrology data, etc. Sets of data input 210A may include data describing different aspects of manufacturing, e.g., a combination of metrology data and sensor data, a combination of metrology data and manufacturing parameters, combinations of some metrology data, some manufacturing parameter data and some sensor data, etc.

[0097] In some embodiments, data set generator 272A may generate a first data input corresponding to a first set of historical metrology data 264A and/or a first set of design rule data 265A to train, validate, or test a first machine learning model. Data set generator 272A may generate a second data input corresponding to a second set of historical metrology data 264B and/or a second set of design rule data 265B to train, validate, or test a second machine learning model.

[0098] In some embodiments, data set generator 272A generates a data set (e.g., training set, validating set, testing set) that includes one or more data inputs 210A (e.g., training input, validating input, testing input) and may include one or more target outputs 220A that correspond to the data inputs 210A. The data set may also include mapping data that maps the data inputs 210A to the target outputs 220A. In some embodiments, data set generator 272A may generate data for training a machine learning model configured to output realistic synthetic microscopy image data, by generating data sets including output microscopy image data 268. Data inputs 210A may also be referred to as “features,” “attributes,” or “information.” In some embodiments, data set generator 272A may provide the data set to training engine 182, validating engine 184, or testing engine 186, where the data set is used to train, validate, or test the machine learning model (e.g., synthetic data generator 174, one of the machine learning models that are included in model 190, ensemble model 190, etc.).

[0099] System 200B containing data set generator 272B (e.g., data set generator 172 of FIG. 1) creates data sets for one or more machine learning models (e.g., model 190 of FIG. 1). Data set generator 272B may create data sets (e.g., data input 210B) using historical data. Example data set generator 272B is configured to generate data sets for a machine learning model configured to take as input predictive microscopy image data and produce as output anomaly prediction data. Analogous data set generators (or analogous operations of data set generator 272B) may be utilized for machine learning models configured to perform different functions, e.g., a machine learning model configured to receive as input sensor data and predicted metrology data, a machine learning model configured to receive as input target metrology data (e.g., a target microscopy image) and produce as output estimated conditions or processing operation recipes that may generate a device matching the input target data, etc. Data set generator 272B may share features and/or function with data set generator 272A.

[00100] Data set generator 272B may generate data sets to train, test, and validate a machine learning model. The machine learning model is provided with set of historical synthetic microscopy data 262A (e.g., output synthetic data from synthetic data generator 174, output from a model trained using data sets from data set generator 272A, etc.) as data input 210B. The machine learning model may include two or more separate models (e.g., the machine learning model may be an ensemble model). The machine learning model may be configured to generate output data indicated performance of the processing chamber, such as an indication of an anomaly present in the processing equipment. In some embodiments, training may not include providing target output to the machine learning model. Data set generator 272B may generate data sets to train an unsupervised machine learning model, e.g., a model configured to receive as input synthetic microscopy data and generate as output clustering data, outlier detection data, anomaly detection data, etc.

[00101] In some embodiments, data set generator 272B generates a data set (e.g., training set, validating set, testing set) that includes one or more data inputs 210B (e.g., training input, validating input, testing input). Data inputs 210B may also be referred to as “features,” “attributes,” or “information.” In some embodiments, data set generator 272B may provide the data set to the training engine 182, validating engine 184, or testing engine 186, where the data set is used to train, validate, or test the machine learning model (e.g., model 190 of FIG. 1). Some embodiments of generating a training set are further described with respect to FIG. 4A.

[00102] In some embodiments, data set generator 272B may generate a first data input corresponding to a first set of historical sensor data 244A to train, validate, or test a first

machine learning model and the data set generator 272A may generate a second data input corresponding to a second set of historical sensor data 244B to train, validate, or test a second machine learning model.

[00103] Data inputs 210B to train, validate, or test a machine learning model may include information for a particular manufacturing chamber (e.g., for particular substrate manufacturing equipment). In some embodiments, data inputs 210B may include information for a specific type of manufacturing equipment, e.g., manufacturing equipment sharing specific characteristics. Data inputs 210B may include data associated with a device of a certain type, e.g., intended function, design, produced with a particular recipe, etc. Training a machine learning model based on a type of equipment, device, recipe, etc. may allow the trained model to generate plausible synthetic sensor data in a number of settings (e.g., for a number of different facilities, products, etc.).

[00104] In some embodiments, subsequent to generating a data set and training, validating or testing a machine learning model using the data set, the model may be further trained, validated, or tested, or adjusted (e.g., adjusting weights or parameters associated with input data of the model, such as connection weights in a neural network).

[00105] FIG. 3 is a block diagram illustrating system 300 for generating output data (e.g., synthetic data 162 of FIG. 1), according to some embodiments. In some embodiments, system 300 may be used in conjunction with a machine learning model configured to generate synthetic microscopy image data (e.g., synthetic data generator 174 of FIG. 1). In some embodiments, system 300 may be used in conjunction with a machine learning model to determine a corrective action associated with manufacturing equipment. In some embodiments, system 300 may be used in conjunction with a machine learning model to determine a fault of manufacturing equipment. In some embodiments, system 300 may be used in conjunction with a machine learning model to cluster or classify substrates. System 300 may be used in conjunction with a machine learning model with a different function than those listed, associated with a manufacturing system.

[00106] At block 310, system 300 (e.g., components of predictive system 110 of FIG. 1) performs data partitioning (e.g., via data set generator 172 of server machine 170 of FIG. 1) of data to be used in training, validating, and/or testing a machine learning model. In some embodiments, training data 364 includes historical data, such as historical metrology data, historical design rule data, historical classification data (e.g., classification of whether a product meets performance thresholds), historical microscopy image data, etc. In some embodiments, e.g., when utilizing synthetic microscopy images generated by a trained

machine learning model to train a second machine learning model, training data 364 may include synthetic microscopy image data, e.g., generated by synthetic data generator 174 of FIG. 1. Training data 364 may undergo data partitioning at block 310 to generate training set 302, validation set 304, and testing set 306. For example, the training set may be 60% of the training data, the validation set may be 20% of the training data, and the testing set may be 20% of the training data.

[00107] The generation of training set 302, validation set 304, and testing set 306 may be tailored for a particular application. For example, the training set may be 60% of the training data, the validation set may be 20% of the training data, and the testing set may be 20% of the training data. System 300 may generate a plurality of sets of features for each of the training set, the validation set, and the testing set. For example, if training data 364 includes sensor data, including features derived from sensor data from 20 sensors (e.g., sensors 126 of FIG. 1) and 10 manufacturing parameters (e.g., manufacturing parameters that correspond to the same processing runs(s) as the sensor data from the 20 sensors), the sensor data may be divided into a first set of features including sensors 1-10 and a second set of features including sensors 11-20. The manufacturing parameters may also be divided into sets, for instance a first set of manufacturing parameters including parameters 1-5, and a second set of manufacturing parameters including parameters 6-10. Either target input, target output, both, or neither may be divided into sets. Multiple models may be trained on different sets of data.

[00108] At block 312, system 300 performs model training (e.g., via training engine 182 of FIG. 1) using training set 302. Training of a machine learning model and/or of a physics-based model (e.g., a digital twin) may be achieved in a supervised learning manner, which involves providing a training dataset including labeled inputs through the model, observing its outputs, defining an error (by measuring the difference between the outputs and the label values), and using techniques such as deep gradient descent and backpropagation to tune the weights of the model such that the error is minimized. In many applications, repeating this process across the many labeled inputs in the training dataset yields a model that can produce correct output when presented with inputs that are different than the ones present in the training dataset. In some embodiments, training of a machine learning model may be achieved in an unsupervised manner, e.g., labels or classifications may not be supplied during training. An unsupervised model may be configured to perform anomaly detection, result clustering, etc.

[00109] For each training data item in the training dataset, the training data item may be input into the model (e.g., into the machine learning model). The model may then process the

input training data item (e.g., a number of measured dimensions of a manufactured device, a cartoon picture of a manufactured device, etc.) to generate an output. The output may include, for example, a synthetic microscopy image. The output may be compared to a label of the training data item (e.g., an actual microscopy image of the device associated with the measured dimensions).

[00110] Processing logic may then compare the generated output (e.g., synthetic image) to the label (e.g., actual image) that was included in the training data item. Processing logic determines an error (i.e., a classification error) based on the differences between the output and the label(s). Processing logic adjusts one or more weights and/or values of the model based on the error.

[00111] In the case of training a neural network, an error term or delta may be determined for each node in the artificial neural network. Based on this error, the artificial neural network adjusts one or more of its parameters for one or more of its nodes (the weights for one or more inputs of a node). Parameters may be updated in a back propagation manner, such that nodes at a highest layer are updated first, followed by nodes at a next layer, and so on. An artificial neural network contains multiple layers of “neurons”, where each layer receives as input values from neurons at a previous layer. The parameters for each neuron include weights associated with the values that are received from each of the neurons at a previous layer. Accordingly, adjusting the parameters may include adjusting the weights assigned to each of the inputs for one or more neurons at one or more layers in the artificial neural network.

[00112] System 300 may train multiple models using multiple sets of features of the training set 302 (e.g., a first set of features of the training set 302, a second set of features of the training set 302, etc.). For example, system 300 may train a model to generate a first trained model using the first set of features in the training set (e.g., sensor data from sensors 1-10, metrology measurements 1-10, etc.) and to generate a second trained model using the second set of features in the training set (e.g., sensor data from sensors 11-20, metrology measurements 11-20, etc.). In some embodiments, the first trained model and the second trained model may be combined to generate a third trained model (e.g., which may be a better predictor or synthetic data generator than the first or the second trained model on its own). In some embodiments, sets of features used in comparing models may overlap (e.g., first set of features being sensor data from sensors 1-15 and second set of features being sensors 5-20). In some embodiments, hundreds of models may be generated including models with various permutations of features and combinations of models.

[00113] At block 314, system 300 performs model validation (e.g., via validation engine 184 of FIG. 1) using the validation set 304. The system 300 may validate each of the trained models using a corresponding set of features of the validation set 304. For example, system 300 may validate the first trained model using the first set of features in the validation set (e.g., sensor data from sensors 1-10 or metrology measurements 1-10) and the second trained model using the second set of features in the validation set (e.g., sensor data from sensors 11-20 or metrology measurements 11-20). In some embodiments, system 300 may validate hundreds of models (e.g., models with various permutations of features, combinations of models, etc.) generated at block 312. At block 314, system 300 may determine an accuracy of each of the one or more trained models (e.g., via model validation) and may determine whether one or more of the trained models has an accuracy that meets a threshold accuracy. Responsive to determining that none of the trained models has an accuracy that meets a threshold accuracy, flow returns to block 312 where the system 300 performs model training using different sets of features of the training set. Responsive to determining that one or more of the trained models has an accuracy that meets a threshold accuracy, flow continues to block 316. System 300 may discard the trained models that have an accuracy that is below the threshold accuracy (e.g., based on the validation set).

[00114] At block 316, system 300 performs model selection (e.g., via selection engine 185 of FIG. 1) to determine which of the one or more trained models that meet the threshold accuracy has the highest accuracy (e.g., the selected model 308, based on the validating of block 314). Responsive to determining that two or more of the trained models that meet the threshold accuracy have the same accuracy, flow may return to block 312 where the system 300 performs model training using further refined training sets corresponding to further refined sets of features for determining a trained model that has the highest accuracy.

[00115] At block 318, system 300 performs model testing (e.g., via testing engine 186 of FIG. 1) using testing set 306 to test selected model 308. System 300 may test, using the first set of features in the testing set (e.g., sensor data from sensors 1-10), the first trained model to determine the first trained model meets a threshold accuracy (e.g., based on the first set of features of the testing set 306). Responsive to accuracy of the selected model 308 not meeting the threshold accuracy (e.g., the selected model 308 is overly fit to the training set 302 and/or validation set 304 and is not applicable to other data sets such as the testing set 306), flow continues to block 312 where system 300 performs model training (e.g., retraining) using different training sets corresponding to different sets of features (e.g., sensor data from different sensors). Responsive to determining that selected model 308 has an accuracy that

meets a threshold accuracy based on testing set 306, flow continues to block 320. In at least block 312, the model may learn patterns in the training data to make predictions or generate synthetic data, and in block 318, the system 300 may apply the model on the remaining data (e.g., testing set 306) to test the predictions or synthetic data generation.

[00116] At block 320, system 300 uses the trained model (e.g., selected model 308) to receive current data 322 (e.g., current metrology data 166 of FIG. 1, such as measurements from an in-situ metrology device) and determines (e.g., extracts), from the output of the trained model, output data 324 (e.g., synthetic data 162 of FIG. 1). A corrective action associated with the manufacturing equipment 124 of FIG. 1 may be performed in view of output data 324. In some embodiments, current data 322 may correspond to the same types of features in the historical data used to train the machine learning model. In some embodiments, current data 322 corresponds to a subset of the types of features in historical data that are used to train selected model 308 (e.g., a machine learning model may be trained using a number of metrology measurements, and configured to generate output based on a subset of metrology measurements).

[00117] In some embodiments, operations of using the trained model at block 320 may not include providing current data 322 to selected model 308. In some embodiments, selected model 308 may be configured to generate synthetic microscopy image data. Training may include providing true microscopy image data to the machine learning model. The training data (e.g., training set 302) may include attribute data. Attribute data includes information labeling training data, such as an indication of which tool the data is associated with, type and ID of sensors, indication of service lifetime of the tool (e.g., time elapsed since tool installation, time elapsed since a previous maintenance event, etc.), indication of a fault or pending fault in the manufacturing equipment that may be reflected in the training data, product type or design, target characteristics of output image, etc. Use of selected model 308 may include providing instructions to the model to generate synthetic microscopy image data. Use of selected model 308 may include providing one or more attributes. Data generated may conform with the one or more attributes, e.g., synthetic data may be generated that resembles data from a particular tool, data collected when a fault is present in the manufacturing equipment, data collected from a particular product design, image data of a target level of contrast or brightness, etc.

[00118] In some embodiments, the performance of a machine learning model trained, validated, and tested by system 300 may deteriorate. For example, a manufacturing system associated with the trained machine learning model may undergo a gradual change or a

sudden change. A change in the manufacturing system may result in decreased performance of the trained machine learning model. A new model may be generated to replace the machine learning model with decreased performance. The new model may be generated by altering the old model by retraining, by generating a new model, etc.

[00119] In some embodiments, one or more of the acts 310-320 may occur in various orders and/or with other acts not presented and described herein. In some embodiments, one or more of acts 310-320 may not be performed. For example, in some embodiments, one or more of data partitioning of block 310, model validation of block 314, model selection of block 316, or model testing of block 318 may not be performed.

[00120] FIG. 3 depicts a system configured for training, validating, testing, and using one or more machine learning models. The machine learning models are configured to accept data as input (e.g., set points provided to manufacturing equipment, sensor data, metrology data, etc.) and provide data as output (e.g., predictive data, corrective action data, classification data, etc.). Partitioning, training, validating, selection, testing, and using blocks of system 300 may be executed similarly to train a second model, utilizing different types of data.

Retraining may also be done, utilizing current data 322 and/or additional training data 346.

[00121] FIGS. 4A-C are flow diagrams of methods 400A-C associated with training and utilizing machine learning models, according to certain embodiments. Methods 400A-C may be performed by processing logic that may include hardware (e.g., circuitry, dedicated logic, programmable logic, microcode, processing device, etc.), software (such as instructions run on a processing device, a general purpose computer system, or a dedicated machine), firmware, microcode, or a combination thereof. In some embodiment, methods 400A-C may be performed, in part, by predictive system 110. Method 400A may be performed, in part, by predictive system 110 (e.g., server machine 170 and data set generator 172 of FIG. 1, data set generators 272A-B of FIGS. 2A-B). Predictive system 110 may use method 400A to generate a data set to at least one of train, validate, or test a machine learning model, in accordance with embodiments of the disclosure. Methods 400B-C may be performed by predictive server 112 (e.g., predictive component 114) and/or server machine 180 (e.g., training, validating, and testing operations may be performed by server machine 180). In some embodiments, a non-transitory machine-readable storage medium stores instructions that when executed by a processing device (e.g., of predictive system 110, of server machine 180, of predictive server 112, etc.) cause the processing device to perform one or more of methods 400A-C.

[00122] For simplicity of explanation, methods 400A-C are depicted and described as a series of operations. However, operations in accordance with this disclosure can occur in

various orders and/or concurrently and with other operations not presented and described herein. Furthermore, not all illustrated operations may be performed to implement methods 400A-C in accordance with the disclosed subject matter. In addition, those skilled in the art will understand and appreciate that methods 400A-C could alternatively be represented as a series of interrelated states via a state diagram or events.

[00123] FIG. 4A is a flow diagram of a method 400A for generating a data set for a machine learning model, according to some embodiments. Referring to FIG. 4A, in some embodiments, at block 401 the processing logic implementing method 400A initializes a training set T to an empty set.

[00124] At block 402, processing logic generates first data input (e.g., first training input, first validating input) that may include one or more of sensor, manufacturing parameters, metrology data, etc. In some embodiments, the first data input may include a first set of features for types of data and a second data input may include a second set of features for types of data (e.g., as described with respect to FIG. 3). Input data may include historical data and/or synthetic data in some embodiments.

[00125] In some embodiments, at block 403, processing logic optionally generates a first target output for one or more of the data inputs (e.g., first data input). In some embodiments, the input includes one or more metrology measurements and the target output is a microscopy image. In some embodiments, the input includes a cartoon image of a device (e.g., generated using a combination of metrology measurements and one or more rules of design) and the target output is a microscopy image. In some embodiments, the first target output is predictive data. In some embodiments, input data may be in the form of sensor data and target output may be a list of components likely to be faulty, as in the case of a machine learning model configured to identify failing manufacturing systems. In some embodiments, no target output is generated (e.g., an unsupervised machine learning model capable of grouping or finding correlations in input data, rather than requiring target output to be provided).

[00126] At block 404, processing logic optionally generates mapping data that is indicative of an input/output mapping. The input/output mapping (or mapping data) may refer to the data input (e.g., one or more of the data inputs described herein), the target output for the data input, and an association between the data input(s) and the target output. In some embodiments, such as in association with machine learning models where no target output is provided, block 404 may not be executed.

[00127] At block 405, processing logic adds the mapping data generated at block 404 to data set T, in some embodiments.

[00128] At block 406, processing logic branches based on whether data set T is sufficient for at least one of training, validating, and/or testing a machine learning model, such as synthetic data generator 174 or model 190 of FIG. 1. If so, execution proceeds to block 407, otherwise, execution continues back at block 402. It should be noted that in some embodiments, the sufficiency of data set T may be determined based simply on the number of inputs, mapped in some embodiments to outputs, in the data set, while in some other embodiments, the sufficiency of data set T may be determined based on one or more other criteria (e.g., a measure of diversity of the data examples, accuracy, etc.) in addition to, or instead of, the number of inputs.

[00129] At block 407, processing logic provides data set T (e.g., to server machine 180) to train, validate, and/or test machine learning model 190. In some embodiments, data set T is a training set and is provided to training engine 182 of server machine 180 to perform the training. In some embodiments, data set T is a validation set and is provided to validation engine 184 of server machine 180 to perform the validating. In some embodiments, data set T is a testing set and is provided to testing engine 186 of server machine 180 to perform the testing. In the case of a neural network, for example, input values of a given input/output mapping (e.g., numerical values associated with data inputs 210A) are input to the neural network, and output values (e.g., numerical values associated with target outputs 220A) of the input/output mapping are stored in the output nodes of the neural network. The connection weights in the neural network are then adjusted in accordance with a learning algorithm (e.g., back propagation, etc.), and the procedure is repeated for the other input/output mappings in data set T. After block 407, a model (e.g., model 190) can be at least one of trained using training engine 182 of server machine 180, validated using validating engine 184 of server machine 180, or tested using testing engine 186 of server machine 180. The trained model may be implemented by predictive component 114 (of predictive server 112) to generate predictive data 168 for performing signal processing, to generate synthetic data 162, or for performing a corrective action associated with manufacturing equipment 124.

[00130] FIG. 4B is a flow diagram of a method 400B for generating and utilizing synthetic microscopy image data, according to some embodiments. At block 410 of method 400B, processing logic receives first data. The first data includes indications of a plurality of dimensions of a manufactured device. The first data may be generated from measured or predicted metrology data associated with a product (e.g., manufactured device). The first data may have been generated based on metrology measurements taken in a non-destructive

measurement process. In some embodiments, a manufacturing system (e.g., used to produce the manufactured device) may be associated with one or more trained machine learning models. A trained machine learning model may be configured to accept as input sensor data, manufacturing parameters, process operation recipe specifications, or the like, and produce as output one or more predicted measurements of the manufactured device. The first data may be derived from these predicted measurements.

[00131] In some embodiments, a manufacturing system may include an in-situ metrology system (e.g., components configured to determine or infer metrology measurements of a product undergoing processing). In-situ metrology may include spectral reflectance data of a substrate, may include processing of data by a machine learning model, etc. The first data may be derived from in-situ metrology data. In some embodiments, a manufacturing system may include an integrated metrology system (e.g., components configured to measure or infer measurements of a manufactured device after a processing operation or between processing operations, without exposing the device to ambient atmosphere). Integrated metrology may include optical measurements, spectral data, etc. The first data may be derived from integrated metrology measurements. In some embodiments, a manufacturing system may include an inline metrology system (e.g., a metrology system coupled to the processing portion of a manufacturing system). The first data may be derived from inline metrology data.

[00132] In some embodiments, measured or predicted metrology data may be provided to a cartoon generator. Example output of a cartoon generator and its operation is discussed in more detail in connection with FIG. 5E. A cartoon generator may receive predicted or measured data indicating dimensions of a manufactured device and data indicating design rules of the manufactured device. Design rules may include the arrangement of structures in a system, e.g., a mask may be situated above a gate, etc. Design rules may include expected shapes of structures, e.g., a spacer may be expected to be rectangular, a gate trapezoidal, etc. Design rules may include relationships between structures, e.g., the width of a structure may be the width of two spacers and the space of a gate, etc. Design rules may include other property information, such as composition of a structure. Design rules may include any other indication that assists in generating an indication of position, size, properties, or shape of structures in a manufactured device.

[00133] A cartoon generator may incorporate design rule data and metrology data and/or sensor data (e.g., measured, predicted by a machine learning model, etc.). The cartoon generator may generate a cartoon image (e.g., an unrealistic, simplified image, a synthetic primitive image, etc.) which indicates predicted placements and sizes of structures of the

manufactured device. In some embodiments, a cartoon generator may be provided with data from multiple processing operations (e.g., several processing operations associated with the same manufactured device) to improve predictions and generated images of the device. In some embodiments, the cartoon generator may incorporate rules of design to infer additional measurements not provided by a metrology system, e.g., may infer sizes of internal structures from rules of design and measurements of external structures. In some embodiments, the cartoon may present a view of the manufactured device that may only be imaged directly by destructive means, e.g., a cross sectional view. The cartoon generator may receive metrology data generated from non-destructive means, e.g., optical measurements of an exterior surface of the manufactured device.

[00134] At block 412, processing logic provides the first data to a trained machine learning model. The model may be configured to accept the first data indicative of one or more metrology measurements of a manufactured product and generate a synthetic microscopy image of the product. At block 414, processing logic receives, from the trained machine learning model, a synthetic microscopy image associated with the manufactured device. The synthetic microscopy image is generated in view of the first data. The machine learning model may be configured to generate a synthetic image similar to true images (e.g., images of manufactured devices taken by microscopy equipment) used to train the model. In some embodiments, training the machine learning model may include providing cross-sectional, top-down, side-on, or another viewing angle image data to the machine learning model. In some embodiments, training the machine learning model may include providing scanning electron microscope, transmission electron microscope, or another microscopy method images to the machine learning model.

[00135] In some embodiments, the trained machine learning model may comprise a neural network. In some embodiments, the trained machine learning model may comprise a generator model. In some embodiments, the trained machine learning model may comprise the generator of a generative adversarial network (GAN). In some embodiments, the machine learning model may be an image-to-image GAN.

[00136] At block 416, processing logic performs one or more actions responsive to receiving the synthetic microscopy image. The actions may include outputting the synthetic microscopy image to a display (e.g., alerting a user). The actions may further include performing one or more operations on the synthetic microscopy image.

[00137] Operations performed on the synthetic microscopy image may include measuring a feature of the synthetic microscopy image. The machine learning model generating the

synthetic image may be configured to generate realistic images associated with a manufactured device. In some embodiments, accurate measurements of structures, similar to measurements that would be taken from a true image of the device, may be generated from the synthetic microscopy image. Measurement of a feature, structure, distance, etc., in the synthetic microscopy image may be used to calculate a dimension of the manufactured device. In some embodiments, the operations performed on the synthetic microscopy image include inputting the synthetic microscopy image into another trained machine learning model that may output a prediction, estimate, etc. based on the synthetic microscopy image.

[00138] In some embodiments, a corrective action may be taken in view of the synthetic microscopy image, in view of measurements of the image, in view of a calculated dimension of the manufactured device, in view of an output of a trained machine learning models that processes the synthetic microscopy image, etc. In some embodiments, the corrective action may include scheduling maintenance, e.g., corrective or preventative maintenance. In some embodiments, the corrective action may include updating a process recipe, a cleaning recipe, a seasoning recipe, etc. In some embodiments, the corrective action may include providing an alert to a user, e.g., if an anomaly exists in the input data to the machine learning model or in the output image.

[00139] In some embodiments, methods also include training the machine learning model to generate plausible microscopy images. Further details of training and operation of an example image generator are discussed further in connection with FIGS. 4C and 5C.

[00140] FIG. 4C is a flow diagram of a method 400C for generating and using synthetic microscopy image data, according to some embodiments. At block 420, processing logic provides historical data including metrology data (e.g., in-situ metrology data, inline metrology data, etc.) and historical microscopy image data (e.g., cross-sectional SEM image data) as training input to train a first machine learning model. The first machine learning model may be a GAN. The first machine learning model may be an image-to-image GAN. Input data may be provided along with one or more associated attributes, e.g., data indicating tool ID, sensor ID, process recipe, service lifetime, properties of the target output image, etc. The GAN may train a generator model utilizing a discriminator model. Metrology data may include data from many types of sensors associated with a manufacturing system, processing chamber, etc. In some embodiments, metrology data may include in-situ metrology data, inline metrology data, integrated metrology data, or the like.

[00141] At block 421, processing logic provides data indicative of one or more attributes of a target synthetic microscopy image data to the trained first machine learning model. The

attributes provided may reflect one or more processing or image conditions of interest, e.g., one or more conditions where a large amount of synthetic data is to be generated. A set of random or pseudo-random numbers may be provided to the trained first machine learning model. The random input may be used as a seed for generation of synthetic data. At block 422, processing logic receives output from the trained first machine learning model. The output includes synthetic microscopy image data. The output data may also include data indicative of one or more associated attributes. Operations of blocks 421 and 422 may share features with operations of FIG. 4B.

[00142] At block 423, processing logic provides the output from the trained first machine learning model as training input to train a second machine learning model. In some embodiments, the output data is provided with historical microscopy image data, e.g., true microscopy image data collected from one or more manufactured products. Synthetic data in some embodiments may be utilized to augment true data. Processing logic provides data indicative of at least one of the one or more attributes as target output to train a second machine learning model. In some embodiments, synthetic data is to be generated for training a model to predict a fault, an anomaly, or predict performance of a manufacturing equipment that has been in service for an amount of time. In some embodiments, synthetic data may be generated associated with a particular tool, sensor, product design, etc. Such information may be provided to train the second machine learning model as attribute data.

[00143] At block 424, processing logic provides current microscopy image data to the trained second machine learning model. The trained second machine learning model may be configured to accept as input microscopy image data and produce as output predictive data, e.g., predicted metrology data, predicted anomalies in a product, predicted faults in a manufacturing system, predicted processing operation progress, etc. The second machine learning model may receive as input synthetic (e.g., predicted) microscopy image data, true microscopy image data, etc. At block 425, predictive data output is received from the trained second machine learning model. At block 426, a corrective action is performed in view of the output from the trained second machine learning model. The corrective action may include scheduling maintenance of processing equipment, updating a process recipe, sending an alert to a user, etc.

[00144] FIGS. 5A-B are depictions of processes and architecture of training and operating generative adversarial networks, according to some embodiments. FIG. 5A depicts a simple GAN 500A. In training, input data 502 is provided to discriminator 508. Discriminator 508 is configured to distinguish whether input data 502 is true data or synthetic data. Discriminator

508 is trained until it achieves an acceptable accuracy. Accuracy parameters may be tuned based on application, for example, the volume of training data available.

[00145] In some embodiments, generator 506 may be provided with input data 502 (e.g., drawn from the same data set as the data used to train discriminator 508) to train generator 506 to produce plausible synthetic data. Generator 506 may be provided with noise 504, e.g., random input, such as a fixed-length vector of pseudo-random values. Generator 506 uses the random input as a seed to generate synthetic data (e.g., synthetic microscopy images). Generator 506 provides the synthetic data to discriminator 508. Further input data 502 (e.g., true data drawn from the same set as the data used to train discriminator 508) is also provided to discriminator 508. Discriminator 508 attempts to distinguish input data 502 from synthetic data provided by generator 506.

[00146] Discriminator 508 provides classification results (e.g., whether each data set supplied to discriminator 508 has been labeled as true or synthetic) to classification verification module 510. Classification verification module 510 determines whether one or more data sets has been labeled correctly by discriminator 508. Feedback data indicative of labeling accuracy is provided both to discriminator 508 and generator 506. Both generator 506 and discriminator 508 are updated in view of the information received from classification verification module 510. Generator 506 is updated to generate synthetic data that is more successful at replicating features of input data 502, e.g., to generate synthetic data that is more often labeled as true data by discriminator 508. Discriminator 508 is updated to improve accuracy of distinguishing true from synthetic data. Training processes may be repeated until generator 506 reaches an accuracy threshold, e.g., until generator 506 produces a large enough portion of data that is not correctly classified by discriminator 508.

[00147] FIG. 5B is a block diagram depicting operating processes of an example GAN 500B for generating synthetic microscopy image data, according to some embodiments. In some embodiments, example GAN 500B may include many features discussed in connection with FIG. 5A.

[00148] In some embodiments, GAN 500B includes a set of generators 520 and a set of discriminators 530. In some embodiments, discriminators 530 are trained by supplying them with input data 536. Discriminators 530 are configured to distinguish between true data and synthetic data. Generators 520 may be configured to generate synthetic data. Generators 520 may be seeded with noise 512, e.g., random or pseudo-random input.

[00149] In some embodiments, GAN 500B may include multiple generators 520 and/or multiple discriminators 530. Discriminators 530 may be configured to accept output data

from different generators or sets of generators. In some embodiments, generators 520 may be configured to generate attribute data via attribute generator 522 and associated data (e.g., synthetic microscopy image data) via feature generator 526. In some embodiments, feature generator 526 is configured to generate normalized data (e.g., synthetic microscopy data with brightness values varying from zero to one), and a min/max generator is configured to generate a minimum and maximum value for the data. In some embodiments, the approach of separating a min/max generator from feature generator 526 may improve the performance of generators 520.

[00150] In some embodiments, noise 512 may be provided to attribute generator 522 and/or feature generator 526. In some embodiments, a different set of noise (e.g., a different set of random inputs) may be provided to each generator of generators 520. In some embodiments, output of attribute generator 522 (e.g., synthetic attribute data) may be provided to auxiliary discriminator 532. Auxiliary discriminator 532 may determine if the combination of attribute values are likely to be associated with true data. A preliminary determination may be performed, saving processing power of generating and/or discriminating synthetic data from feature generator 526. Output of generators 520 may all be provided to discriminator 534. Discriminator 534 may distinguish true data from synthetic data, including attribute data, feature (e.g., microscopy image) data, etc. In some embodiments, a min/max generator may be an optional feature, e.g., GAN 500B may be configured to normalize data from feature generator 526, accompanied by min/max values, or configured to produce data values via feature generator 526.

[00151] In some embodiments, target attributes 523 may be provided to generators 520. Target attributes may define properties of a target microscopy image to be generated. In some embodiments, target attributes may include features of the image to be generated, e.g., image quality, contrast, brightness, etc. In some embodiments, target attributes include target metrology measurements, one or more target rules of design, etc. In some embodiments, target measurements and/or rules of design may be provided to generators 520 by providing a cartoon image (e.g., like that depicted in FIG. 5E) to generators 520. Generators 520 may be configured to generate realistic synthetic microscopy images, sharing features in common with the provided attributes (e.g., including shapes similar to a provided cartoon).

[00152] In some embodiments, feature generator 526 may include a machine learning generator model designed to generate image data, e.g., synthetic microscopy image data of a manufactured product. In some embodiments, GAN 500B may comprise a conditional GAN. In a conditional GAN, during training, the discriminator may be provided with a synthetic

image and a true image, and may be configured to determine whether the synthetic image is an acceptable representation of the true image. In some embodiments, the generator may be additionally updated by an additional loss function. In some embodiments, the output of the generator (e.g., as generated from a cartoon image related to a manufactured product) may be compared to a true microscopy image of the related product. In some embodiments, the images may be compared on a pixel-to-pixel basis, a feature-to-feature basis, or the like. The generator may be penalized for differences between input and output on the basis of the sum of the absolute values of the error (e.g., L1 loss function), on the basis of the sum of the squares of the error (e.g., L2 loss function), etc.

[00153] In some embodiments, a target shape or pattern may be included in synthetic data. For example, an anomalous structure in one or more imaged products may be included in future simulated images, e.g., for training a second machine learning model. In some embodiments, feature generator 526 may accept instructions to facilitate generation of synthetic data included a target shape or pattern. A range or distribution of locations (e.g., spatially), values, shapes, etc., may be provided to feature generator 526. Feature generator 526 may generate data with a target shape or pattern expressed in accordance with a distribution of properties, e.g., the anomalous may appear in many sets of synthetic data in a range of locations, reaching a range of heights, with a range of widths.

[00154] In some embodiments, synthetic data (e.g., data output from generators 520) may be utilized to train one or more machine learning models. In some embodiments, synthetic data may be utilized to train a machine learning model configured for event detection, e.g., configured to determine if synthetic image data is within normal variations or indicative of a system anomaly. In some embodiments, synthetic data may be utilized to generate a robust model – synthetic data may be generated with a higher noise level than true data, and a machine learning model trained with the synthetic data may be capable of providing useful output for a wider variety of input than a model trained only on true data. In some embodiments, synthetic data may be utilized to test a model for robustness. In some embodiments, synthetic data may be utilized to generate a model for anomaly detection and/or classification. In some embodiments, synthetic data may be provided to train a machine learning model as training input, and one or more attribute data (e.g., attribute data indicating a system fault) may be provided to train the machine learning model as target output. In some embodiments, attribute data may include an indication of a service lifetime of a manufacturing system, e.g., time since installation of the system, number of products

produced since installation of the system, time or number of products produced since the last maintenance event, etc.

[00155] FIG. 5C is a flow diagram of a method for training a machine learning model (e.g., a GAN) to generate realistic synthetic microscopy images, according to some embodiments. At block 540, a true image (e.g., a microscopy image taken of a manufactured device using a microscopy technique) is generated. The image may be generated using any microscopy technique, e.g., scanning electron microscopy, transmission electron microscopy, etc. The image may be of a device or structure, including a cross-sectional image, a top-down image, etc. In some embodiments, images used for training may be selected for use because the images exhibit target properties, e.g., contrast, clarity, sharpness, etc. In some embodiments, one or more properties of the image (e.g., contrast, sharpness, etc.) may be classified as an attribute.

[00156] At block 542, one or more critical dimensions (CDs) are measured from the microscopy image. Measured dimensions may include height of a structure, width of a structure, etc. Measurement may include determining the edge of a structure (e.g., using a machine learning image processing model), determining a distance on image from one edge of the structure to the opposite edge, and calculating the size of the imaged device from the size of the image.

[00157] At block 544, measured CDs and design rules (of block 543) are provided to a cartoon generator. The cartoon generator is configured to synthesize the CDs and rules of design to generate a cartoon image of the manufactured device. The cartoon image may carry the information of both the measured CDs and the design rules. In some embodiments, the cartoon image presents accurate dimensions in a simplified picture. An example cartoon image is depicted in FIG. 5E.

[00158] At block 546, the cartoon is supplied to the synthetic image generator which is to be trained. The synthetic image generator may be included in a GAN. The synthetic image generator may be included in a conditional GAN. The synthetic image generator may be included in an image-to-image (e.g., pix2pix) GAN. The synthetic image generator generates a synthetic image at block 548.

[00159] At block 552, CDs are measured from the synthetic image. In some embodiments, the same CDs may be measured as those measured at block 542. In some embodiments, the synthetic image may resemble the true image, and similar CDs may be measureable from the two images. Operations of block 552 may have features in common with operations of block 542.

[00160] At block 554, additional loss terms are included in analysis. For example, the true image and the synthetic image may be compared pixel-to-pixel. In some embodiments, an L1 loss function may be applied to the synthetic image, e.g., a penalty may be calculated to aid in training the machine learning model. Data indicative of differences between synthetic and true images (e.g., loss term, differences in measured CDs, etc.) may be provided to the image generator. The generator may be updated (e.g., weights between neurons in a neural network adjusted) to improve the similarity of true and synthetic images.

[00161] FIG. 5D depicts a flow diagram of a method 500D for generating synthetic microscopy images using a trained machine learning-based image generator, according to some embodiments. At block 560, a number of critical dimensions (CDs) associated with a manufactured product are provided to processing logic. The CDs provided may be predictive, e.g., generated by a machine learning model associated with the system processing the manufactured product. The CDs provided may be measured during processing of the product, e.g., by an in-situ metrology device. The CDs provided may be measured between or after processing operations, e.g., by inline, integrated, or standalone metrology systems. In some embodiments, the product CDs provided may be generated using non-destructive means, e.g., optical measurements, predictions based on sensor data, etc.

[00162] At block 562, the product CDs and design rules (of block 561) are provided to a cartoon generator. The cartoon generator may have similar function to that of a cartoon generator of block 544 of FIG. 5C. The cartoon generator produces as output a cartoon image associated with the manufactured device. The cartoon image may be indicative of provided metrology (e.g., CDs) and provided design rules. The cartoon image is provided to a synthetic image generator at block 564.

[00163] The synthetic image generator of block 564 may include components of a GAN (e.g., one or more generators of the GAN), a conditional GAN, an image-to-image GAN, a neural network or other machine learning model, etc. The synthetic image generator is configured to accept a cartoon image indicative of structures of a manufactured device and generate as output a realistic synthetic microscopy image 566 of the device.

[00164] FIG. 5E depicts an example cartoon image 500E of a manufactured device to be provided as input to a synthetic image generator, according to some embodiments. The cartoon image reproduces some information that may be determined from a microscopy image of a device, e.g., an SEM or TEM image. Image 500E depicts similar structures as may be seen when performing a cross-sectional TEM imaging of a logic device. Cartoons depicting other views, other devices, other angles, etc., are within the scope of this disclosure.

[00165] Cartoon image 500E includes a number of structures. Device structures stand atop pedestals 570. The device may include a gate 572. The gate may be surrounded by spacers 574, and topped by mask 576. Deposition material 578 may be disposed on top of mask 576. Other devices, other designs, etc., are within the scope of this disclosure.

[00166] A cartoon generator may be or include a trained machine learning model or a drawing module that uses one or more rules to generate synthetic cartoon (e.g., simple line drawing) images. A cartoon generator may be provided with a number of rules of design that are used to approximate the shape of a manufactured device. Design rules may be determined based on intended device properties, properties measured by a metrology system, etc. In some embodiments, design rules may be approximations of the dimensions of the device. For example, a two-dimensional cross section of mask 576 in a SEM image of a device may be roughly trapezoidal, with variations from a strict trapezoid caused by deposition/etch physics, deposition/etch inhomogeneity, influence from adjacent structures, etc. The cartoon generator may be configured to approximate the true cross sectional shape of the mask with a square, situated above gate 572 with top edge matching with the top edges of spacers 574. Similarly, other structures may be approximated by the cartoon generator as being simple shapes, when in reality they may be more complicated. For example, deposition 578 may be approximated as a half-circle, spacers 574 as parallelograms or rectangles, pedestals 570 as rectangles, etc.

[00167] A cartoon generator may receive a number of measurements of a device from a manufacturing system, from a metrology system, etc. The cartoon generator may also receive a number of rules of design. For example, a cartoon generator may be provided with a set of rules regarding relative placement of structures, e.g., mask 576 may be placed as a square structure above and with the same width as gate 572, upper deposition 578 may be hemispherical in the generated cartoon with radius matching the top edge of spacers 574 and mask 576, etc. The rules of design may be approximations of true structural shapes. In some embodiments, the synthetic image generator may convert approximate shapes into more realistic shapes. For example, the cartoon generator may be configured to represent pedestals 570 as rectangles, and the synthetic image generator may be trained (based on supplied microscopy image training data) to generate an image with pedestals that have been etched (e.g., as shown in image 500E).

[00168] A cartoon generator may combine supplied metrology measurements with rules of design to generate the cartoon image. Metrology data may be available for some dimensions of the device, and not others. The cartoon generator may use design rules to fill in for metrology that is not provided. For example, metrology may provide a measurement of a

structure, e.g., height 580. Synthesizing the height and known rules of design, the cartoon generator may produce an image with all internal structures, e.g., by estimating (or incorporating another metrology measurement to define) width, placing a half circle representing silicon dioxide deposition on top of the structure, and incorporating intended design rules (e.g., relative width of mask/gate and spacers, basic shapes and placement of structures, etc.) to produce an image of the entirety of a device.

[00169] In some embodiments, cartoon image 500E may be provided to a machine learning image generator (e.g., generator of an image-to-image GAN). The machine learning model may generate as output a synthetic microscopy image of the manufactured device. In some embodiments, metrology measurements that were not measured during/after processing, metrology measurement not provided to the cartoon generator, etc., may be calculated from the synthetic image. For example, successive width measurement in various positions of a structure may be measured from the synthetic image, etch depth of pedestals 570 may be quantified, etc.

[00170] FIG. 6 is a block diagram illustrating a computer system 600, according to some embodiments. In some embodiments, computer system 600 may be connected (e.g., via a network, such as a Local Area Network (LAN), an intranet, an extranet, or the Internet) to other computer systems. Computer system 600 may operate in the capacity of a server or a client computer in a client-server environment, or as a peer computer in a peer-to-peer or distributed network environment. Computer system 600 may be provided by a personal computer (PC), a tablet PC, a Set-Top Box (STB), a Personal Digital Assistant (PDA), a cellular telephone, a web appliance, a server, a network router, switch or bridge, or any device capable of executing a set of instructions (sequential or otherwise) that specify actions to be taken by that device. Further, the term "computer" shall include any collection of computers that individually or jointly execute a set (or multiple sets) of instructions to perform any one or more of the methods described herein.

[00171] In a further aspect, the computer system 600 may include a processing device 602, a volatile memory 604 (e.g., Random Access Memory (RAM)), a non-volatile memory 606 (e.g., Read-Only Memory (ROM) or Electrically-Erasable Programmable ROM (EEPROM)), and a data storage device 618, which may communicate with each other via a bus 608.

[00172] Processing device 602 may be provided by one or more processors such as a general purpose processor (such as, for example, a Complex Instruction Set Computing (CISC) microprocessor, a Reduced Instruction Set Computing (RISC) microprocessor, a Very Long Instruction Word (VLIW) microprocessor, a microprocessor implementing other types

of instruction sets, or a microprocessor implementing a combination of types of instruction sets) or a specialized processor (such as, for example, an Application Specific Integrated Circuit (ASIC), a Field Programmable Gate Array (FPGA), a Digital Signal Processor (DSP), or a network processor).

[00173] Computer system 600 may further include a network interface device 622 (e.g., coupled to network 674). Computer system 600 also may include a video display unit 610 (e.g., an LCD), an alphanumeric input device 612 (e.g., a keyboard), a cursor control device 614 (e.g., a mouse), and a signal generation device 620.

[00174] In some embodiments, data storage device 618 may include a non-transitory computer-readable storage medium 624 (e.g., non-transitory machine-readable medium) on which may store instructions 626 encoding any one or more of the methods or functions described herein, including instructions encoding components of FIG. 1 (e.g., predictive component 114, corrective action component 122, model 190, etc.) and for implementing methods described herein.

[00175] Instructions 626 may also reside, completely or partially, within volatile memory 604 and/or within processing device 602 during execution thereof by computer system 600, hence, volatile memory 604 and processing device 602 may also constitute machine-readable storage media.

[00176] While computer-readable storage medium 624 is shown in the illustrative examples as a single medium, the term "computer-readable storage medium" shall include a single medium or multiple media (e.g., a centralized or distributed database, and/or associated caches and servers) that store the one or more sets of executable instructions. The term "computer-readable storage medium" shall also include any tangible medium that is capable of storing or encoding a set of instructions for execution by a computer that cause the computer to perform any one or more of the methods described herein. The term "computer-readable storage medium" shall include, but not be limited to, solid-state memories, optical media, and magnetic media.

[00177] The methods, components, and features described herein may be implemented by discrete hardware components or may be integrated in the functionality of other hardware components such as ASICs, FPGAs, DSPs or similar devices. In addition, the methods, components, and features may be implemented by firmware modules or functional circuitry within hardware devices. Further, the methods, components, and features may be implemented in any combination of hardware devices and computer program components, or in computer programs.

[00178] Unless specifically stated otherwise, terms such as “receiving,” “performing,” “providing,” “obtaining,” “causing,” “accessing,” “determining,” “adding,” “using,” “training,” “reducing,” “generating,” “correcting,” or the like, refer to actions and processes performed or implemented by computer systems that manipulates and transforms data represented as physical (electronic) quantities within the computer system registers and memories into other data similarly represented as physical quantities within the computer system memories or registers or other such information storage, transmission or display devices. Also, the terms “first,” “second,” “third,” “fourth,” etc. as used herein are meant as labels to distinguish among different elements and may not have an ordinal meaning according to their numerical designation.

[00179] Examples described herein also relate to an apparatus for performing the methods described herein. This apparatus may be specially constructed for performing the methods described herein, or it may include a general purpose computer system selectively programmed by a computer program stored in the computer system. Such a computer program may be stored in a computer-readable tangible storage medium.

[00180] The methods and illustrative examples described herein are not inherently related to any particular computer or other apparatus. Various general purpose systems may be used in accordance with the teachings described herein, or it may prove convenient to construct more specialized apparatus to perform methods described herein and/or each of their individual functions, routines, subroutines, or operations. Examples of the structure for a variety of these systems are set forth in the description above.

[00181] The above description is intended to be illustrative, and not restrictive. Although the present disclosure has been described with references to specific illustrative examples and embodiments, it will be recognized that the present disclosure is not limited to the examples and embodiments described. The scope of the disclosure should be determined with reference to the following claims, along with the full scope of equivalents to which the claims are entitled.

CLAIMS

What is claimed is:

1. A method, comprising:
receiving first data indicating a plurality of dimensions of a manufactured device;
providing the first data to a trained machine learning model;
receiving, from the trained machine learning model, a synthetic microscopy image associated with the manufactured device, wherein the synthetic microscopy image is generated in view of the first data; and
performing at least one of (i) outputting the synthetic microscopy image to a display or (ii) performing one or more operations on the synthetic microscopy image.
2. The method of claim 1, further comprising:
receiving second data indicating a subset of the plurality of dimensions indicated by the first data;
receiving third data indicating one or more rules of design of the manufactured device; and
providing the second data and the third data to a model configured to generate the first data in view of the second data and the third data.
3. The method of claim 2, wherein:
the first data comprises a synthetic primitive image; and
the second data comprises predictive data generated by a manufacturing system associated with the manufactured device.
4. The method of claim 3, wherein the second data comprises metrology data generated from a non-destructive measurement process.
5. The method of claim 1, wherein the trained machine learning model comprises a generator of a generative adversarial network.
6. The method of claim 1, wherein the synthetic microscopy image comprises a synthetic image of a cross section of the manufactured device, wherein the synthetic image resembles a microscopy image generated by an electron-based microscopy technique.

7. The method of claim 1, wherein performing the one or more operations on the synthetic microscopy image comprises:
- measuring a feature of the synthetic microscopy image; and
 - calculating a dimension of the manufactured device based on the measurement of the feature of the synthetic microscopy image.
8. The method of claim 7, further comprising causing performance of a corrective action in view of the calculated dimension of the manufactured device, wherein the corrective action comprises one or more of:
- scheduling maintenance;
 - updating a process recipe; or
 - providing an alert to a user.
9. A method, comprising:
- receiving a plurality of microscopy images, wherein each microscopy image of the plurality of microscopy images is of one of a plurality of manufactured devices;
 - receiving first data indicating a plurality of dimensions of the plurality of manufactured devices; and
 - training a machine learning model to generate synthetic microscopy images using the first data and the plurality of microscopy images, wherein training the machine learning model comprises providing the first data to the machine learning model as training input, and providing the plurality of microscopy images to the machine learning model as target output.
10. The method of claim 9, further comprising:
- receiving second data, wherein the second data is based on metrology measurements of the plurality of manufactured devices, and wherein the metrology measurements were generated from one or more non-destructive measurement processes; and
 - providing the second data to a model to generate the first data, wherein the first data comprises a plurality of synthetic primitive images.
11. The method of claim 9, wherein training the machine learning model comprises training a generative adversarial network.

12. The method of claim 9, wherein the plurality of microscopy images comprise cross-sectional images of the manufactured devices, and wherein the microscopy images are generated by electron-based imaging methods.
13. A non-transitory machine-readable storage medium storing instructions which, when executed, cause a processing device to perform operations comprising:
- receiving first data indicating a plurality of dimensions of a manufactured device;
 - providing the first data to a trained machine learning model;
 - receiving, from the trained machine learning model, a synthetic microscopy image associated with the manufactured device, wherein the synthetic microscopy image is generated in view of the first data; and
 - performing at least one of (i) outputting the synthetic microscopy image to a display or (ii) performing one or more operations on the synthetic microscopy image.
14. The non-transitory machine-readable storage medium of claim 13, wherein the operations further comprise:
- receiving second data indicating a subset of the plurality of dimensions indicated by the first data;
 - receiving third data indicating one or more rules of design of the manufactured device; and
 - providing the second data and the third data to a model configured to generate the first data in view of the second data and the third data.
15. The non-transitory machine-readable storage medium of claim 14, wherein:
- the first data comprises a synthetic primitive image; and
 - the second data comprises predictive data generated by a manufacturing system associated with the manufactured device.
16. The non-transitory machine-readable storage medium of claim 14, wherein the second data comprises metrology data generated from a non-destructive measurement process.
17. The non-transitory machine-readable storage medium of claim 13, wherein the trained machine learning model comprises a generator of a generative adversarial network.

18. The non-transitory machine-readable storage medium of claim 13, wherein the synthetic microscopy image comprises a synthetic cross sectional scanning electron microscope image.

19. The non-transitory machine-readable storage medium of claim 13, wherein performing the one or more operations on the synthetic microscopy image comprises:
measuring a feature of the synthetic microscopy image; and
calculating a dimension of the manufactured device based on the measurement of the feature of the synthetic microscopy image.

20. The non-transitory machine-readable storage medium of claim 19, wherein the operations further comprise causing performance of a corrective action in view of the calculated dimension of the manufactured device, wherein the corrective actions comprises one or more of:

- scheduling maintenance;
- updating a process recipe; or
- providing an alert to a user.