

PRODUCTION ANALYSIS MODELING FOR PRODUCT QUALITY DETECTION**Technical Field**

[0001] The present disclosure relates to production analysis modeling for product quality detection. Such techniques can be particularly useful to predict a quality or quality defects associated with a product of a particular manufacturer by modeling production data from a plurality of different manufacturers of the product.

Background

[0002] Artificial neural networks (ANNs) are networks that can process information by modeling a network of neurons, such as neurons in a human brain, to process information (e.g., stimuli) that has been sensed in a particular environment. Similar to a human brain, neural networks typically include a multiple neuron topology (e.g., that can be referred to as artificial neurons). An ANN operation refers to an operation that processes, to perform a given task, inputs using artificial neurons. The ANN operation may involve performing various machine learning algorithms to process the inputs. Example tasks that can be processed by performing ANN operations can include machine vision, speech recognition, machine translation, social network filtering, and/or medical diagnosis.

[0003] A plurality of manufacturing sites provide double belt lamination customers with foam formulations and expertise for the fabrication of sandwich metal panels with a rigid polyurethane or polyisocyanurate core. A good foam formulation distribution is of paramount importance for producing good quality panels and avoid quality claims. In addition, foam formulation bubbling can negatively affect a quality of a panel. Furthermore, over-rolling of a top layer after the deposition of the foam material can occur and negatively affect a quality of a panel. For this reason, suppliers have developed their own foam formulation distributors (also known as pokers) and the suppliers provide them to the panels manufacturers together with the foam formulation. Different foam formulation distributors provide different qualities of foam formulation distribution on different surfaces and/or for end products (e.g., panels) utilized for different functions.

[0004] Among other, appropriate distribution of the foam formulation is critical for producing panels without underlying defects, that over time develop blisters after panel installation and subsequent claims from the downstream customers. The problem is that foam formulation application is currently poorly monitored, if at all. There is currently no quantitative check of the foam formulation application during production.

Summary of the Disclosure

[0005] The present disclosure is directed to using improvements in machine learning technology to predict a property of a product (e.g., quality, effectiveness, defects, failures, etc.). Image based visual analysis utilizing a machine learning model can be utilized to monitor and analyze a production process to predict a property of the product based on production analysis data. The image based visual analysis can utilize a machine learning model to interpret and extract data from captured images by identifying relevant patterns and features within the images. These features can include, but are not limited to: edges, textures, shapes, colors, and/or other visual attributes. A prediction of a property of the product can be received from the machine learning model and used to adjust the production process or to determine whether to reject the product.

[0006] As a specific example, data can be collected from a plurality of different manufacturing sites to generate a machine learning model to predict a quality of a product generated by different manufacturing sites. The machine learning model can be utilized to identify production parameters that may be a cause of particular properties. As used herein, production parameters relate to collected data during a production of a particular product. For example, the production parameters for depositing a foam material (e.g., polyurethane (PUR) or polyisocyanurate (PIR) formulation, etc.) can include, but are not limited to: foam deposition device data, foam deposition stream data, foam surface distance data. Production parameters for quality check of the foam material can include but are not limited to: foam surface bubbling data, over-rolling data, formed foam edge data, and product dimensions data when the product includes a foam material, among other data that can potentially affect a quality of a produced product utilizing the foam material layer. In addition, the machine learning model can generate production parameter ranges for a plurality of production parameters that can be provided to the plurality of different manufacturing sites to ensure a quality level of the product.

[0007] The above summary of the present disclosure is not intended to describe each disclosed embodiment or every implementation of the present disclosure. The description that follows more particularly exemplifies illustrative embodiments. In several places throughout the application, guidance is provided through lists of examples, which examples can be used in various combinations. In each instance, the recited list serves only as a representative group and should not be interpreted as an exclusive list.

Brief Description of the Drawings

[0008] Figure 1 illustrates an example of a system for production analysis modeling for product quality detection.

[0009] Figure 2 is one example diagram illustrating a system for depositing a foam material on an application surface for the production of sandwich panels through a continuous process.

[0010] Figure 3 illustrates different foam material distributors for depositing a foam material on an application surface.

[0011] Figure 4 illustrates an example image of bubbling occurring during a foam material deposition on an application surface.

[0012] Figure 5 illustrates an example of over-rolling during a foam material deposition on an application surface.

[0013] Figure 6 illustrates an example of edge dimension measurements of a product utilizing a foam material on an application surface.

[0014] Figure 7 illustrates an example of a method for production analysis modeling for product quality detection.

[0015] Figure 8 illustrates an example of a machine readable medium for production analysis modeling for product quality detection.

[0016] Figure 9 illustrates an example of a device for production analysis modeling for product quality detection.

Detailed Description

[0017] The present disclosure relates to methods and devices for production analysis modeling for product quality detection, which may utilize machine learning models to predict product properties for one or more products generated with different production analysis data. An example of a machine learning model is an ANN. The ANN can provide learning by forming probability weight associations between an input and an output. The probability weight associations can be provided by a plurality of nodes that comprise the ANN. The nodes together with weights, biases, and/or activation functions can be used to generate an output of the ANN based on the input to the ANN. A plurality of nodes of the ANN can be grouped to form layers of the ANN.

[0018] A machine learning model can be a function or equation for identifying patterns in data. A machine learning module can be a plurality of machine learning models

utilized together to identify patterns in data. In a specific example, a machine learning module can be organized as a neural network. A neural network can include a set of instructions that can be executed to recognize patterns in data. Some neural networks can be used to recognize underlying relationships in a set of data in a manner that mimics the way that a human brain operates. A neural network can adapt to varying or changing inputs such that the neural network can generate an acceptable result in the absence of redesigning the output criteria.

[0019] Production of particular products can utilize different conditions during the production process. The production conditions during the production process can have different effects on a quality of the product. Different types of production conditions can have a different quantity of effects the end product produced. The production conditions can be monitored by different types of devices. For example, imaging devices, timing devices, sensor devices, and/or other types of devices can be utilized to monitor the different types of conditions to generate production data for the product.

[0020] The production data can be generated by a plurality of different manufacturing sites and implemented into a uniform format (e.g., production analysis data, etc.) to allow the different manufacturing sites to provide federated data to be utilized to generate or train a machine learning model. The production analysis data can include image data collected during a production process, production setting data collected during the production process, and/or environmental data collected during the production process. The machine learning model can utilize the production data or production analysis data and corresponding quality data associated with the product produced to generate production ranges that can be utilized by each of the plurality of manufacturing sites to increase a quality of the product. In this way, a product review of a particular product can be generated by the machine learning model to identify one or more of the production data that are attributed to a particular defect or particular quality level of the product to be reviewed by the product review.

[0021] As used herein, the singular forms “a”, “an”, and “the” include singular and plural referents unless the content clearly dictates otherwise. Furthermore, the word “may” is used throughout this application in a permissive sense (e.g., having the potential to, being able to), not in a mandatory sense (e.g., must). The term “include,” and derivations thereof, mean “including, but not limited to.”

[0022] As will be appreciated, elements shown in the various embodiments herein can be added, exchanged, and/or eliminated so as to provide a number of additional embodiments of the present disclosure. In addition, as will be appreciated, the proportion and the relative

scale of the elements provided in the figures are intended to illustrate certain embodiments of the present invention and should not be taken in a limiting sense.

[0023] Figure 1 illustrates an example of a system 100 for production analysis modeling for product quality detection. System 100 illustrates a system for applying a foam material on an application surface. Although the system 100 illustrates a specific system for applying a foam material on a particular surface, the disclosure is not so limited. For example, other types of systems can utilize the functions and/or features described herein in a similar way for production analysis modeling for product quality detection of other types of products.

[0024] The system 100 includes a double belt lamination (DBL) system 102 that can dispense a chemical compound or foam material that can be utilized to form a rigid polyurethane (PUR) or polyisocyanurate (PIR) core foam material on a surface. As used herein a foam material refers to a substance that includes gas bubbles trapped within a liquid or solid matrix. In a first example, the foam material includes a substance with gas bubbles trapped within the liquid or solid prior to distribution and/or a substance that includes gas bubbles trapped within the liquid or solid after a chemical reaction or after distribution of the foam material. The foam material can be distributed onto a surface when the foam material is in a liquid foam state. The liquid foam state can solidify and become a solid foam state on the surface over a period of time.

[0025] The DBL system 102 can include a foam distribution device that can distribute the chemical compound or foam material onto a surface. The DBL system 102 is further described with reference to Figure 2. In general, the DBL system 102 includes a foam dispersion device that can deposit the foam material onto a surface (e.g., application surface, portion of a surface, etc.) that is transported along a path of the foam dispersion device. In this way, the surface is transported across a foam dispersion area to receive the foam material from the foam distribution device.

[0026] The surface can be positioned on a transportation system to bring the surface to different areas to allow different substances, chemicals, or layers to be applied. For example, the transportation system can transport the surface to a first area to receive an adhesive promoting chemical and to a second area to receive the foam material. In these embodiments, the foam material can be deposited on the adhesive promoting chemical to ensure adhesion of the foam material to the application surface.

[0027] Transporting the surface from the first location to the second location can be monitored by a timing device to determine the quantity of time it takes the surface to move

from the first location to the second location. As described further in reference to Figure 5, a top application surface can be applied to the foam material on the surface. In these embodiments, the timing device can determine the quantity of time between the deposit of the foam material and the application of the top application surface on the foam material. As described further in reference to Figure 2, the system 100 can include additional sensors to monitor a quantity of time it takes for the surface to move from the location to receive the adhesive promoting chemical from an adhesive distribution device to a different location to receive the foam material from the foam distribution device. The chemical deposited by the adhesive distribution device can undergo a particular chemical reaction. In this way, the quantity of time can be utilized to determine a state of the chemical reaction when the surface reaches the foam distribution device. In addition, the timing device can be utilized to determine a quantity of time between when the foam material is deposited on the application surface and when an additional application surface is applied to the foam material. As described further herein, the timing of the application of the additional application surface to the foam material can affect a quality of the product.

[0028] The system 100 can include an imaging device 112. The imaging device 112 can be a device to capture images of the surface to identify properties of the foam material deposited on the surface by the foam distribution device. The imaging device 112 can include one or more of: a video camera, a still image camera, a thermal imaging camera, a hyperspectral camera, and/or other type of device that can captures images and/or video of the surface. The imaging device 112 can be a standardized imaging device that can be utilized by each of the plurality of manufacturing sites to create federated data from each of the plurality of manufacturing sites. In a similar way, the location and/or angle of the imaging device 112 can be a standardized location and/or angle to capture an image of the surface, of the foam or of the panel at the same or similar position from double band lamination line. In this way, the data captured by the imaging device 112 can be correlated to data captured at different manufacturing sites.

[0029] In a similar way, the system 100 can include a light source 110. The light source 110 can generate different wavelengths of light to further highlight particular features of the surface. In some embodiments, the light source 110 can be selected or altered based on the type of imaging device 112 and/or the type of data to be collected. In some embodiments, the light source 110 can be a standardized light source that is utilized by each of the plurality of manufacturing sites to create federated data from each of the plurality of manufacturing sites. In a similar way, the location and/or angle of the light source 110 can be a standardized

location and/or angle to provide light on the surface, of the foam or of the panel at the same or similar position from the double band lamination line. In this way, the data captured by the imaging device 112 can be correlated to data captured at different manufacturing sites since the lighting in the images will have the same or similar properties.

[0030] The system 100 can include a control panel 106 that can be utilized by a user 108. The control panel 106 can be utilized to display notifications generated by the system 100 to notify the user 108 when current conditions or metrics of the system 100 are outside a particular range. As described further herein, the data collected during the production of the surface and/or a product utilizing the surface can be utilized to generate production ranges that can be utilized by the system 100.

[0031] The images captured by the imaging device 112 can be provided to a machine learning model 114 operating on the edge computing device 116. The machine learning model 114 can be utilized to analyze the received images from the imaging device 112. In other embodiments, the machine learning model 114 can be utilized to organize the data collected by the system 100 into a data file that can be correlated to an end product utilizing the surface. For example, humidity data, temperature data, foam distribution data of a chemical layer, layer uniformity data of the foam material, and/or time data between depositing the foam layer and applying an additional application surface on the foam material can be correlated together and associated with a product that utilized the particular surface. In this way, a quality of the surface portion can be determined over a period of time and correlated to the data associated with the surface.

[0032] The system 100 can include an edge computing device 116. In some examples, the edge computing device 116 is a computing device that includes a processor resource and a machine readable medium to store instructions that are executed by the processor resource to perform particular functions. The edge computing device 116 can be utilized to communicate with a remote device 124. The remote device 124 can be a cloud device that can receive data from a plurality of manufacturing sites to increase the data set used to train the machine learning model 114 for a particular product and/or for portions of a product such as the surface. The edge computing device 116 can be utilized to remove data associated with the particular manufacturing site that the site does not want to be shared with other manufacturing sites.

[0033] In other embodiments, the edge computing device 116 can utilize production ranges (e.g., production condition ranges, condition thresholds, etc.) to monitor the data provided by the machine learning model 114. When data received by the machine learning

model 114 is outside a threshold range, the edge computing device 116 can send a notification to the control panel 106 to notify the user 108. In this way, alterations can be made to the production data and/or production settings in real time. The panel can be discarded or marked as second quality when the edge computing device 116 determines the production data of the particular product were outside a threshold range of data. As described herein, the threshold ranges can be provided by the remote device 124 when the remote device 124 is utilizing a machine learning model.

[0034] As used herein, production settings can be adjustable settings that can define production parameters of how the system 100 deposits the foam material on the surface and/or how a product is produced that includes the foam material. For example, the production settings can include, but are not limited to: a position of the imaging device 112 and/or light source 110 to alter or influence the images, a type of a foam distribution device, a flow rate of the foam distribution device, a backpressure provided by the foam distribution device, a mixture ratio of a foam material deposited by the foam distribution device, a quantity of a component of the foam material, a gel time of the foam material, a contact time between the foam material and the application surface, an operation time duration of the foam distribution device, a temperature of the foam material when deposited by the foam distribution device, and/or a line speed of the surface moving from a first location to a second location to alter or influence the distribution. In this way, the system 100 can alter or adjust the production settings to alter or adjust how the foam distribution device applies the foam material to the surface of the application surface. In this way, the production settings can be altered to ensure that production data is within the threshold range of data provided by the machine learning model.

[0035] The remote device 124 can receive data from the edge computing device 116 and receive data organized in the same way from a plurality of other manufacturing sites 120. In this way, the remote device 124 can utilize a machine learning model to perform advanced data analytics 118 on the data received from the edge computing device 116. The remote device 124 can utilize this data from the edge computing device 116 and the other manufacturing sites 120 to generate support knowledge to the control panel 106. As described further herein, the support knowledge can include product review analysis for a specific product produced at a particular time and/or production data ranges that can be utilized by the edge computing device 116 to generate real time notifications to the control panel 106.

[0036] Figure 2 is one example diagram illustrating a system 202 for depositing a foam material 239 on an application surface 234 for the production of sandwich panels

through a continuous process. The system 202 can include a plurality of elements for producing a product that includes the foam material 239. For example, the system 202 can include elements for generating panels that include the foam material. In some embodiments, the system 202 includes a corona device 231. As used herein, a corona device 231 can be a surface treatment device that uses corona discharge to modify surface properties of the application surface 234. In some embodiments, the corona device 231 can improve a surface activation utilizing corona discharge (e.g., low-temperature plasma, etc.) with reactive ions, electrons, and/or radicals. In some embodiments, the corona device 231 includes cleaning treatments, adhesion improvement treatments, among other treatments to improve the adhesion of chemicals to a surface of the application surface 234. In some embodiments, a transportation system 236 can be utilized to move the application surface 234 and/or top application surface 235 along a pathway to allow the application surface 234 and/or top application surface 235 to interact with different components of the system 202.

[0037] In some embodiments, the transportation system 236 can move the application surface 234 from the corona device 231 to an adhesive distribution device 232. The adhesive distribution device 232 can apply an adhesive promotion layer (e.g., primer, etc.) to the application surface 234 that has been treated by the corona device 231. In these embodiments, the transportation system 236 can move the application surface 234 from the adhesive distribution device 232 to a foam distribution device 233 that can distribute a foam material 239 on the application surface 234. In some embodiments, the foam distribution device 233 can deposit the foam material 239 onto the adhesive promotion layer.

[0038] As described herein, the foam material 239 can be utilized to form a rigid polyurethane (PUR) or polyisocyanurate (PIR) core foam material on the application surface 234. The foam material 239 can be deposited as a substance that includes gas bubbles trapped within a liquid. The liquid foam material 239 can solidify into a solid foam state between the application surface 234 and the top application surface 235.

[0039] As described further herein, an imaging device (e.g., imaging device 112 as referenced in Fig. 1, etc.) can be utilized to monitor the foam distribution device 233 and the foam material 239 applied to the application surface 234. In this way, the type of the foam distribution device 233 can be determined, a performance of the foam distribution device 233 can be monitored during the distribution of the foam material 239, a chemical composition of the foam material 239 can be monitored, and/or the surface properties of the foam material 239 can be monitored while the transportation system 236 is moving the application surface 234 and/or top application surface 235.

[0040] The foam material 239 can expand or increase in height between the foam distribution device 233 and a contact point 240. The contact point 240 can be a location where the foam material 239 makes physical contact with the top application surface 235. In some embodiments, the quantity of time between the deposition of the foam material 239 and the contact point 240 can be 1 second to 40 seconds. More particularly, the quantity of time between the deposition of the foam material 239 and the contact point 240 can be 10 seconds to 30 seconds. As described further in reference to Figure 5, a laser or similar sensor device can be utilized to monitor a location of the contact point 240 to prevent over-rolling by utilizing the contact point 240 to alter a speed of the transportation system 236. In a specific example, a time of flight sensor can be utilized with a laser to determine when the foam material 239 makes physical contact with the top application surface 235. For example, a time of flight sensor can determine a quantity of time it takes the laser to reach the contact point 240 and the quantity of time can be utilized to determine the distance and/or location of the contact point 240.

[0041] In this way, the imaging device and/or other sensors can be utilized to monitor the performance of the foam distribution device 233, the surface properties of the foam material 239, a quantity of time between the distribution of the foam material 239 and the contact point 240, and/or chemical composition or chemical ratio of the foam material 239. The performance of the foam distribution device 233, the surface properties of the foam material 239, a quantity of time between the distribution of the foam material 239 and the contact point 240, and/or chemical composition or chemical ratio of the foam material 239 can be utilized to generate production analysis data and/or utilized to generate notifications when the data is outside threshold data provided by a machine learning model.

[0042] In some embodiments, the transportation system 236 can move the foam material 239 and the application surface 234 and top application surface 235 to a cutter 237. The cutter 237 can be utilized to cut panels of specific length. As described further herein, the edge portion 238 at the cut portion can be analyzed with an imaging device to determine if there are existing defects and/or whether the cut edge meets the particular size and dimension specifications. In some embodiments, the foam material 239 is allowed to partially solidify into a solid state prior to performing a cut at the cutter 237. As described further herein with respect to Figure 6, the edge portion 238 can be further analyzed to include additional production analysis data.

[0043] Figure 3 illustrates different foam material distributors 333-1, 333-2 for depositing a foam material 339 on an application surface 334. As described herein, the

application surface 334 can be prepared to receive the foam material 339 utilizing a corona device and/or applying an adhesive promoting layer. The foam material distributors 333-1, 333-2 can be different types of distributors that apply the foam material 339 to the application surface 334 at different flow rates, angles, and/or distances from the application surface 334. In some embodiments, the type of foam material distributor can affect a quality of an end product based on a use of the end of product. The type of foam material distributor can affect the properties of the end product. These different properties may be beneficial or detrimental to the effectiveness of the product based on how the product is used.

[0044] In some embodiments, the foam material distributors 333-1, 333-2 can be utilized as part of a system for applying the foam material 339 to the application surface 334 (e.g., DBL system 102 as referenced in Figure 1, system 202 as referenced in Figure 2, etc.). In some embodiments, an imaging device (e.g., imaging device 112 as referenced in Figure 1, etc.) can be utilized to identify the type of the foam material distributors 333-1, 333-2. In some embodiments, the imaging device can utilize physical or functional features of the foam material distributors 333-1, 333-2 to determine the type of the foam material distributor. For example, the imaging device can capture images of the size, shape, angle of depositing the foam material 339, flow rate of depositing the foam material 339, and/or other features of the foam material distributors 333-1, 333-2 that can indicate a particular model or type of foam material distributor. In other embodiments, a code (e.g., barcode, QR code, etc.) can be captured by the imaging device to identify the type of the foam material distributors 333-1, 333-2.

[0045] As described herein, the imaging device can be utilized to capture images of the foam material distributors 333-1, 333-2 and the deposited foam material 339 during the foam distribution process. In some embodiments, the imaging device can monitor a flow rate of the foam material 339 being deposited from the foam material distributors 333-1, 333-2. As used herein, the flow rate of the foam material 339 refers to a quantity of foam material 339 being deposited by the foam material distributors 333-1, 333-2 over a period of time. During operation of the foam material distributors 333-1, 333-2, the outlets (e.g., nozzles, etc.) that distribute the foam material 339 can become clogged with foam material 339 such that the flow rate decreases. In some embodiments, the imaging device can be utilized to capture images that can be utilized to determine when the flow rate falls below a threshold flow rate. As illustrated by foam material distributor 333-1 the flow rate of a first dispense stream 342-1 may be less than the second dispense stream 342-2.

[0046] In some embodiments, the threshold flow rate can be based on a machine learning model that can base the threshold flow rate on identified flow rates and quality metrics of corresponding end products from a plurality of manufacturing sites. That is, the flow rate from the outlets can be monitored and provided as production analysis data. In these embodiments, the production analysis data can be utilized by the machine learning model with corresponding quality data to determine the threshold flow rates. In this way, the threshold flow rate can be updated by the machine learning model as additional data is provided to the machine learning model from the plurality of different manufacturing sites. As described herein, a notification can be generated when a flow rate of a dispense stream from an outlet is below a threshold flow rate such that the production can be stopped to clean the outlets to increase the flow rate before restarting production. In other embodiments, portions of the end product can be identified as not meeting particular manufacturer specifications when the flow rate of the dispense stream is below a threshold flow rate during production of the portions of the end product.

[0047] In some embodiments, the imaging device can capture a surface image of the foam material 339 once the foam material 339 is applied to the application surface 334. In some embodiments, the surface image can be utilized to determine surface properties associated with each of a plurality of dispense streams. For example, as illustrated by foam material distributor 333-2, a surface image captured by an imaging device can determine a first width 343-1 associated with a first dispense stream and a second width 343-2 associated with a second stream. In some embodiments, a corresponding width can be identified for a plurality of additional dispense streams.

[0048] In some embodiments, the plurality of widths associated with the plurality of dispense streams can be utilized to determine a quantity of the foam material 339 deposited for each of the plurality of dispense streams or dispense nozzles. In some embodiments, the plurality of widths can be utilized to ensure that the foam material 339 extends across the entire surface of the application surface 334 without spaces between the foam material 339 dispensed by a first dispense stream and the foam material 339 dispensed by a second dispense stream. In some embodiments, the plurality of widths associated with a particular surface can be utilized with the production analysis data provided to a machine learning model. In other embodiments, the plurality of widths can be compared to the threshold widths provided by the machine learning model.

[0049] As described further herein, the surface images captured by the imaging device can also be utilized to determine a chemical composition and/or mixture ratio

associated with the foam material 339. For example, the imaging device can be a hyperspectral imaging device. As used herein, a hyperspectral imaging device is an optical device designed to capture and analyze the electromagnetic spectrum in a large number of narrow, contiguous spectral bands or channels. In some embodiments, a hyperspectral imaging device can capture a plurality of spectral bands spanning the visible, near-infrared, and/or infrared portions of the spectrum. In these embodiments, each band or channel in a captured hyperspectral image corresponds to a specific narrow range of wavelengths. The spectral information can be utilized to determine a chemical composition or chemical ratio of the foam material 339 during the production process.

[0050] In a similar way as other production analysis data, the hyperspectral images captured can be included as production analysis data for a particular surface and/or particular product. This data can be utilized by the machine learning model with corresponding quality data to generate chemical composition threshold ranges that can be utilized to monitor the chemical formulation of the foam material 339 during production.

[0051] Figure 4 illustrates an example image 444 of bubbling 445 occurring during a foam material deposition on an application surface. As described herein, the imaging device can capture surface images of the foam material 439. In some embodiments, the flow rate of the foam material 439 or other factors associated with dispensing the foam material 439 on the application surface can cause a bubbling 445. The bubbling 445 can be caused by gasses (e.g., air, etc.) that are trapped within the foam material 439 and/or between the foam material 439 and the application surface.

[0052] In some embodiments, the trapped gasses that cause the bubbling 445 can cause defects 446 within the foam material 439 when fully formed. For example, the foam material 439 can cure to a point where the liquid foam material 439 turns into a solid foam material 439. In these embodiments, the solid foam material 439 can include the defects 446, which can result in a relatively lower quality compared to foam materials 439 without the defects 446.

[0053] In some examples, the imaging device can capture surface images of the foam material 439 that can be analyzed to determine the bubbling 445 based on color differences or color pattern along the surface of the foam material 439. For example, the bubbling 445 can be identified as a different color in the surface images captured by the imaging device. In these examples, the surface images can be monitored during the production process to determine when a color difference along the surface of the foam material exceeds a threshold color difference. The threshold color difference can be provided by the machine learning

model that is based on federated data from the plurality of manufacturing sites. In some embodiments, a notification can be generated when the color difference monitored during the production process exceeds the threshold color difference. This can allow a setting associated with the foam dispersion device to be altered. For example, the flow rate of the foam material 439 can be altered, a height between a dispense nozzle and the application surface can be adjusted, and/or other production settings can be altered to lower the bubbling 445.

[0054] Figure 5 illustrates an example system 502 experiencing over-rolling 551 during a foam material deposition on an application surface. In some embodiments, the system 502 can include the same or similar elements as the DBL system 102 illustrated in Figure 1, and/or the system 202 as referenced in Figure 2. For example, the system 502 can include a distribution device 533 to deposit a foam material 539 on an application surface 534. In addition, the system 502 can include a transportation system 536 to move the application surface 534 to different locations. In some embodiments, the transportation system 536 can move the application surface 534 with the foam material 539 to a contact point where a top application surface 535 makes contact with the foam material 539. Furthermore, the transportation system 536 can move the application surface 534, foam material 539, and top application surface 535 to a cutter.

[0055] As described herein, an imaging device (e.g., imaging device 112 as referenced in Figure 1, etc.) can be utilized to monitor the foam distribution device 533 and the foam material 539 applied to the application surface 534. In this way, the type of the foam distribution device 533 can be determined, a performance of the foam distribution device 533 can be monitored during the distribution of the foam material 539, and/or the surface properties of the foam material 539 can be monitored while the transportation system 536 is moving the application surface 534 and/or top application surface 535.

[0056] The foam material 539 can expand or increase in height between the foam distribution device 533 and a contact point 540 between the foam material 539 and the top application surface 535. The quantity of time between the deposition of the foam material 539 and the contact point 540 is usually known as contact time. In some processing conditions, the difference between the gel time and the contact time can be approximately 5 seconds to 7 seconds. In this way, the imaging device can be utilized to monitor the performance of the foam distribution device 533, the surface properties of the foam material 539, a quantity of time between the distribution of the foam material 539 and the contact point 540 the difference between the measured gel time and the contact time and/or chemical composition or chemical ratio of the foam material 539.

[0057] When the difference between the gel and contact time is not well under control over-rolling 551 can be present. As used herein, the term over-rolling 551 refers to a situation when the foam material 539 rolls over the top application surface 535 in the opposite direction with respect to the one in which the facing itself travels. The over-rolling 551 can result in an end product (e.g., panel, etc.) with compromised mechanical properties and/or include the potential of showing shrinkage or too low compressive strength values. Over-rolling 551 can be controlled by monitoring a difference between gel-time and contact-time. In some embodiments, a contact time for the foam material 539 can be calculated or measured utilizing a laser to determine when the top application surface interacts with the foam material 539.

[0058] In some embodiments, the gel-time and/or contact-time can include upper and lower threshold values that can be provided by the machine learning model. In some embodiments, the defects associated with an over-rolling 551 can be utilized to determine the upper and lower threshold values such that notifications can be generated when a likely over-rolling 551 has occurred at a particular manufacturing site.

[0059] In some embodiments, the transportation system 536 can move the foam material 539 between the application surface 534 and top application surface 535 to a cutter. The cutter can be utilized to cut an edge with particular size and dimension specifications. As described further herein with reference to Figure 6, the edge portion at the cut portion can be analyzed with an imaging device to determine if there are existing defects and/or whether the cut edge meets the particular size and dimension specifications.

[0060] Figure 6 illustrates an example of edge dimension measurements of a product 660 utilizing a foam material 639 on an application surface. In some embodiments, the product 660 is a panel that includes the foam material 639 between a first application surface and a second application surface. For example, the foam material 639 can be positioned between a top surface and a bottom surface as illustrated in Figure 6. In some embodiments, the imaging device can capture an image of the edge of the product 660 to identify particular edge dimension measurements and/or to identify a quality of the foam material 639. In these embodiments, the foam material 639 can be fully cured or substantially cured such that defects 666, bubbling holes, or other potential quality issues can be observed.

[0061] In some embodiments, the image captured by the imaging device can be analyzed for color irregularities to determine defects 666 or other irregularities within the foam material 639. The image captured by the imaging device can also include hyperspectral information that can be utilized to determine the composition of the foam material. The

image data can be correlated with the production data for the product 660 such that the defects 666 can be correlated to the settings and/or captured images during the production process.

[0062] In some embodiments, the image captured by the imaging device can be analyzed to determine a plurality of different dimension measurements (e.g., measurements “X”, “Y”, “A”, and/or “B”, etc.) and compare the dimension measurements to an industry standard or to a dimension specification for the product 660. For example, a base distance 661 can be compared to a specification base distance to determine if the base distance 661 is within a particular margin of error. In some embodiments, the particular margin of error can be determined based on the specification for the product 660 and/or from the machine learning model.

[0063] In other embodiments, top distances 662 can be distances between a plurality of ridges, a ridge height 663, a first edge dimension 664, and/or a second edge dimension 665 can be determined utilizing an image from the imaging device. In these embodiments, the measurements from the image can be compared to dimension specification measurements for the product 660. In these embodiments, specific features or measurements associated with the first edge dimensions 664 and/or the second edge dimensions 665 can be compared to the dimension specification to ensure that the product 660 is within an acceptable margin of error to the dimension specification.

[0064] In other embodiments, the image from the imaging device can be utilized to identify potential defects that are visible on the top surface or the bottom surface of the final product. For example, the top surface or bottom surface may include ripples or visual defects that can occur in the presence of different defects associated with the foam material 639, an application layer, and/or an adhesive promoting layer. In these embodiments, the ripples or visual defects can be identified from the image by color changes or color patterns across the surface. In these embodiments, the identified defects can be correlated with the data collected during production of the product 660.

[0065] Figure 7 illustrates an example of a method 770 for production analysis modeling for product quality detection. In some examples, the method 770 can be executed by a computing device as described herein. The method 770 can be utilized to identify particular production data that can be a cause of a particular defect and/or identify a threshold range for a particular production data that can be utilized by a particular manufacturing site.

[0066] At step 771, the method 770 can include receiving a review request for a product that includes an identified failure related to a foam material of the product. As used

herein, a review request can be a request to analyze a particular product. The review request can include an identifier that can be utilized to identify production analysis data for the product. As used herein, an identifier can be an indicator or unique identifier that allows the product to be correlated with the production analysis data. In this way, the specific production analysis data (e.g., image data, calculations from the image data, environmental data, production settings data, etc.) utilized during production of the product can be compared to other production analysis data of other products. The identified failure can be an indication of a quality level that is below a threshold quality level. For example, the identified failure can be a portion of the product that is visually or functionally below a threshold quality level for the product.

[0067] The review request can be provided by one of a plurality of different users. For example, the review request can be provided by one of a manufacturer of the product, a customer of the product, a seller of the product, a distributor of the product, among other users associated with the product. The physical product may not be needed to identify the production analysis data for the product. For example, the identifier can be provided within the review request and utilized to identify the production analysis data for the product. The identified failure can be used to (further) train the machine learning model as a known output for the production analysis data for the product as an input. In this way, the production analysis data for the product can be associated with the identified failure data.

[0068] At step 772, the method 770 can include identifying production analysis data associated with a production process for applying the foam material to the product. The production analysis data includes a plurality of data captured during production of the product. In some embodiments, during the application of the foam, application of the top layer, after cutting, and/or after the foam material is dried, among other parts of a production process. For example, the production analysis data can include a plurality of data captured during an application of the foam material to an application surface of the product. In another example, the production analysis data can include a plurality of data captured when a top layer is being applied to the surface of the foam material. Furthermore, the production analysis data can include a plurality of data captured after the foam material has dried. The combination of the production analysis data at the different stages or processes of production can allow a root cause of a defect or identified failure.

[0069] Identifying the production analysis data for a particular product can include utilizing an identifier of the product to extract the production analysis data associated with the production process while producing the product. By identifying the production analysis data

associated with the production process of the product, the data collected during the production of the specific product can be compared to data collected during the production of similar products or products of the same type.

[0070] The production analysis data for the product can include, but is not limited to: thermal imaging data or hyperspectral image data to determine a surface texture of a foam material layer of the type of product, hyperspectral imaging data to determine chemical formulation data for the foam material layer, process timing data associated with a time of depositing the foam material layer, foam deposition device data, foam deposition stream data, foam surface distance data, foam surface bubbling data, over-rolling data, formed foam edge data, and product dimensions data when the product includes a foam material, and/or environmental data at a time when the product was produced at a particular production site. As described herein, identifying the production analysis data for the product can include utilizing an identifier to determine a particular date and time that corresponds to when the product or portion of the product was produced by a particular manufacturer. In this way, the data from the particular manufacturer can be utilized to identify the production analysis data during the particular date and time that produced the product or portion of the product.

[0071] As described herein, the production analysis data can include production data and analysis data during the production of the product and/or production of a plurality of portions of the product. In this way, a failure point (e.g., portion of the product that failed, etc.) of the identified failure can be identified by the machine learning model and the portion of the product that failed can be further analyzed.

[0072] At step 773, the method 770 can include providing the production analysis data for the product to a machine learning model for producing the product to compare a plurality of data from the production analysis data to designated ranges for applying the foam material to the product. Providing the production analysis data to the machine learning model can include utilizing the machine learning model to compare the production analysis data of the product to production analysis data for a plurality of other products. The plurality of other products can be produced in a similar way as the product and may be manufactured by the same or different manufacturing site. For example, the same type of product can be generated or produced at the plurality of different manufacturing sites. In this way, the machine learning model can identify other products that include the same or similar production analysis data to determine when a production condition is outside of a threshold production condition for manufacturing the product. In addition, the machine learning model can utilize the production analysis data to identify a cause of the identified failure. For example, the machine learning

model can identify one or more production data values within the production analysis data that are outside of a threshold range that can be determined or calculated by the machine learning model.

[0073] Training the machine learning model can further include identifying a first plurality of products that include production analysis data that falls within a particular range of the production analysis data of the product that includes the identified failure or defect. Identifying the first plurality of products can include comparing the production analysis data for a plurality of similar products or for a particular type of products. The first plurality of products can be identified as similar production products that were produced under similar conditions as the product (e.g., a product to be analyzed, etc.). The first plurality of products can be products that were manufactured in the same or similar production conditions. In this way, the first plurality of products can be analyzed or utilized to train the machine learning model to identify products that include the same or similar identified failure as the product. The first plurality of products can have different degrees of the identified failure that can be utilized to determine a cause of the identified failure by comparing the degree of the identified failure to the production analysis data of the product and the first plurality of products.

[0074] In these examples, training the machine learning model further comprises identifying a second plurality of products that include the identified failure. Identifying the second plurality of products can include comparing the identified failure of a particular product (e.g., product to be analyzed, etc.) to defects or failures associated with a plurality of other products. The second plurality of products can be identified as similar failure products that include the same or similar type of failure as the particular product to be analyzed. The machine learning model is able to identify the second plurality of products based on features of the identified failure. For example, a “blister” or “bulge” in a surface of the product can have particular features or properties. In this example, the machine learning model can identify the second plurality of products that include a similar “blister” or “bulge”. In these embodiments, the machine learning model can identify the production analysis data associated with the second plurality of products to identify a potential failure of the product. For example, the production analysis data of the product that is similar to the second plurality of products can be identified as a cause of failure. The identified failure and/or cause of the identified failure can be utilized to update and/or train the machine learning model.

[0075] The method 770 can include comparing the identified failure of the product to a failure status of the first plurality of products. In this way, the identified failure can be

provided to the machine learning model and the machine learning model can compare the identified failure to a failure status of the first plurality of products. In some embodiments, a portion of the first plurality of products can be identified as having the same or similar production analysis data and the same or similar defect as the product being analyzed with the identified failure. As described herein, quality data or failure status of the first plurality of products can be compared to the identified failure to determine if there is the same or similar type of failure between the product and the first plurality of products.

[0076] As used herein, a failure status can include an indication of whether the product has an identified failure or does not have an identified failure (e.g., identified defect, etc.). In other embodiments, the failure status can include an indication of a type of failure when there is an identified failure. In these embodiments, comparing the production analysis data of the product to production analysis data corresponding to the second plurality of products. As described herein, the production analysis data or production conditions of the second plurality of products can be compared to the production analysis data or production conditions of the product to identify similarities. The identified similarities can be further analyzed to determine if these production conditions were a cause or potential cause of the identified failure.

[0077] The machine learning model can be trained with production analysis data from a plurality of data sources that are associated with a plurality of different production sites (e.g., manufacturing sites, etc.) that produce elements of the product or similar elements associated with the product. In some examples, the different production sites can manufacture or produce a portion of a product. In these examples, the production analysis data can be generated in a uniform manner to allow the data to be utilized in a federated manner. That is, the data from the plurality of different production sites can be utilized to generate and/or train the machine learning model.

[0078] As described herein, the production analysis data from the plurality of data sources includes foam surface distance data, foam surface bubbling data, and/or over-rolling data when the product includes a foam material. The foam surface distance data, foam surface bubbling data, and/or over-rolling data can be utilized to determine a consistency of a particular foam material at a particular location on an application surface. In this way, the product may have been produced using a particular portion or section of the application surface and the consistency of the foam material layer within that particular portion or section can be identified and associated with the product while other portions or sections not used by the product can be associated with other products. The production analysis data can include

environmental data and process timing data associated with a time of depositing the foam material layer. The environmental data can include, but is not limited to: a humidity at the manufacturing site, a temperature at the manufacturing site, a particular matter concentration at the manufacturing site, and/or other features of the site that relate to the environment or conditions of the manufacturing site.

[0079] As described herein, the process timing data or contact-time can refer to a quantity of time between depositing the foam material and applying a top application surface. In some examples, application of the top application surface can be timed to be applied during a particular stage of a curing process of the foam material such as a gel-time of the foam material. As described herein, a gel-time of the foam material can be monitored and may be affected by a mixture ratio and/or environmental conditions. The process timing data along with the curing time data can be utilized to determine what curing stage the foam material layer was at when the top application surface was applied.

[0080] At step 774, the method 770 can include determining data from the production analysis data that is outside of a designated range identified by the machine learning model. In some examples, the production analysis data can be specific data that are compared between the product and a plurality of other products that include the same or similar identified failure. In other examples, the designated range identified by the machine learning model can be generated based on previously collected data relating to other products that are similar to the product.

[0081] At step 775, the method 770 can include identifying a cause of the identified failure during the production of the product based on the determined data. The determined data can already be outside a defined range of the machine learning model. For example, the machine learning model can generate ranges for the production analysis data based on historical production analysis data and/or identified failures. In this example, the machine learning model can determine that one or more of the data points falls outside these generated ranges and determine that the cause of the failure is due to the one or data points falling outside the generated ranges.

[0082] Figure 8 illustrates an example of a machine readable medium 880 for production analysis modeling for product quality detection. The machine readable medium 880 can be communicatively connected to a processor resource 881 by a communication path 882. In some examples, a communication path 882 can include a wired or wireless connection that can allow communication between devices and/or components within a single device. As used herein, the processor resource 881 can include, but is not limited to: a central

processing unit (CPU), an application specific integrated circuit (ASIC), a field programmable gate array (FPGA), a metal-programmable cell array (MPCA), a semiconductor-based microprocessor, or other combination of circuitry and/or logic to orchestrate execution of instructions 876, 877, 878, 879. In a specific example, the processor resource 881 utilizes a non-transitory computer-readable medium storing instructions 876, 877, 878, 879, that, when executed, cause the processor resource 881 to perform corresponding functions.

[0083] The machine readable medium 880 may be electronic, magnetic, optical, or other physical storage device that stores executable instructions. Thus, a non-transitory machine-readable medium (MRM) (e.g., machine readable medium 880) may be, for example, a non-transitory MRM comprising Random-Access Memory (RAM), read-only memory (ROM), an Electrically Erasable Programmable ROM (EEPROM), a storage drive, an optical disc, and the like. The machine readable medium 880 may be disposed within a controller and/or computing device. In this example, the executable instructions 876, 877, 878, 879, can be “installed” on the device. Additionally, and/or alternatively, the machine readable medium 880 can be a portable, external, or remote storage medium, for example, which allows a computing system to download the instructions 876, 877, 878, 879, from the portable/external/remote storage medium. In this situation, the executable instructions may be part of an “installation package”.

[0084] The machine readable medium 880 includes instructions 876 to train a machine learning model of a production process for applying a foam material to a type of product utilizing production analysis data captured during the production process of the type of product at a plurality of different sites. In these examples, the machine learning model correlates the production analysis data of applying the foam material to a quality level of the foam material for type of product. As described herein, the type of product can include an application layer or application surface that has foam material layer applied during the production process.

[0085] The machine readable medium 880 can include instructions to generate a machine learning model of a production process for a product utilizing production analysis data captured during the production process at a plurality of different sites. The machine learning model can correlate the production analysis data to a quality level of the product. As described herein, a machine learning model can be generated or trained utilizing production data that is provided by a plurality of different manufacturing sites. The different manufacturing sites can each be instructed to collect data in the same or similar way. For

example, the different manufacturing sites can be instructed to collect the same type of data (e.g., infrared images, hyperspectral images, laser measurement data, etc.). In some examples, the different manufacturing sites can be instructed to collect the data a particular time (e.g., quantity of time after depositing a particular layer, etc.). In addition, the different manufacturing sites can be instructed to collect different environmental data during the production of the product.

[0086] The data that is collected by the different manufacturing sites can be organized into production analysis data that can be provided to train or generate the machine learning model as federated data. The different manufacturing sites can be instructed to analyze raw data and provide designated analysis to the machine learning model. For example, the different manufacturing sites can be instructed to calculate a foam surface distance data for a particular portion of a substrate as it moves along a transportation system. In this way, the foam surface distance data can be provided to the machine learning model without having to provide the raw data, which could include sensitive information. In this way, the different manufacturing sites can each provide data to the machine learning model without having to risk providing sensitive information. In some embodiments, raw data refers to unprocessed, unfiltered, and unmodified data collected directly from a source. For example, the raw data can be image data collected directly from an imaging device without being altered or updated. This type of raw data can include sensitive information that may not want to be disclosed to outside sources.

[0087] The machine readable medium 880 includes instructions 877 to provide production analysis data for a particular site to the machine learning model. In these examples, the production analysis data includes image data and environmental data during application of the foam material for the type of product at the particular site over a period of time. In some examples, the machine learning model can be generated or trained using the production analysis data of the different manufacturing sites. The trained machine learning model can be utilized to analyze production of the type of product at a particular site. The particular site can be one of the different manufacturing sites, however, the particular site may also be a different site that did not provide production analysis data to train the machine learning model. The production analysis data for the particular site can be compared to the production analysis data of the different sites to determine if the particular site is producing the product within data ranges calculated by the machine learning model.

[0088] The machine readable medium 880 includes instructions 878 to identify data of the production process based on the production analysis data for the particular site that

includes a value that is outside a determined range of the machine learning model. The plurality of data metrics captured during the production process at the plurality of different sites can include thermal imaging data to determine the foam distribution and the surface uniformity. As described herein, the data metrics captured during the production process at the plurality of different sites can include production settings utilized during the production process. For example, the production settings can be adjustable settings that define production parameters of the mechanical components that are utilized to dispense the foam material layer onto a surface. In addition, the production settings can be settings for collecting the image data or other data to be utilized as production analysis data.

[0089] The plurality of data metrics captured during the production process at the plurality of different sites can include hyperspectral imaging data to determine chemical formulation data for the foam material layer. The plurality of data metrics captured during the production process at the plurality of different sites can be federated data received from the plurality of different sites. As used herein, federated data refers to an approach in which data from multiple sources or entities is kept separate and distributed, while still allowing collaborative analysis and insights to be drawn from the combined data. Instead of centralizing data in a single location or organization, federated data systems enable data to remain decentralized and fragmented across various independent entities or locations. In some embodiments, each entity or organization retains control and ownership of its own data, preserving data privacy and security. Rather than directly sharing or pooling the data, a federated approach involves implementing protocols that enable data analysis and processing to be performed across the distributed data sources without the need for data movement or direct access.

[0090] The machine readable medium 880 includes instructions 879 to generate a notification to alter a production setting of the production process for the particular site to change the value to be within the determined range of the machine learning model. The notification can be an instruction to alter a particular production setting of the production process. In other embodiments, the instruction can perform the alteration without human interaction. Altering the setting of the production process can include sending a notification to a control panel of the particular site to instruct the site to change a particular setting of the production process (e.g., a foam distribution flow rate, foam distribution device cleaning, chemical composition of foam material, etc.) can be adjusted by the control panel or adjusted by a human user. In some examples, a foam material layer can comprise multiple chemicals that can be distributed by a foam distribution device. The flow speed of the distribution

device can alter the foam surface distance, foam surface bubbling, and/or over-rolling of the foam material. In other examples, altering the setting can include updating production process ranges that were utilized by the particular site. For example, the particular site can utilize a first operation time duration of a foam distribution device and the machine learning model can indicate that a second operation time duration of the foam distribution device should be utilized by the particular site instead. As described herein, the foam distribution device can become clogged by the foam material after a particular quantity of time. The updated operation time duration can allow for the foam distribution device to be utilized for longer periods of time or ensure that the flow rate of the foam distribution device does not fall below a threshold flow rate during operation.

[0091] In other examples, altering the setting of the production process can include altering the production process at the particular site. For example, the control panel can be accessed, and production process settings can be altered. In this example, a foam dispersion device setting can be altered to alter the flow rate to a value that is within the flow rate range of the machine learning model. Other types of settings or processes can be altered based on the cause of the identified failure.

[0092] The machine readable medium 880 can include instructions to update the machine learning model utilizing production analysis data captured at the particular site. The production analysis data of the particular site can be utilized to update the machine learning model. The machine learning model can be updated with the production analysis data from the particular site. In these embodiments, the updated machine learning model may make alterations to the production process of the plurality of different sites. For example, data ranges for particular data of the production analysis data may change in view of the production analysis data provided by the particular site. In this example, the updated ranges can be provided to the plurality of different sites.

[0093] Figure 9 illustrates an example of a device 901 for production analysis modeling for product quality detection. In some examples, the device 901 is a computing device that includes a processor resource 981 and a machine readable medium 980 to store instructions 991, 992, 993, 994, 995, that are executed by the processor resource 981 to perform particular functions. Figure 9 illustrates how a computing device can execute instructions to perform functions described herein. The device 901 can be a machine learning model operating on a computing device.

[0094] The device 901 can be communicatively coupled to an imaging device 912 through a communication path 982. As described herein, the imaging device 912 can capture

images of an application surface 934 when a foam material is applied to the application surface 934. The captured images from the imaging device 912 can be sent to the device 901 through the communication path 982 where the captured images can be analyzed.

[0095] The device 901 includes instructions 991 stored by the machine readable medium 980 that is executed by the processor resource 981 to monitor received image data of the application surface 934 during the application of the foam layer on the application surface 934 at the production site. The image data can be received from the imaging device 912 through the communication path 982. The image data can be infrared image data, hyperspectral image data, visual image data, among other types of image data. The image data can be analyzed by a machine learning model (e.g., machine learning model 114 as referenced in Figure 1, etc.) and/or an edge computing device (e.g., edge computing device 116 as referenced in Figure 1, etc.).

[0096] The device 901 includes instructions 992 stored by the machine readable medium 670 that is executed by the processor resource 981 to calculate production analysis data associated with applying the foam layer on the application surface based on the image data. The production data can include, but are not limited to: a production setting, an environmental feature of the different site over the period of time, a foam distribution, a surface uniformity of the foam layer, and a quantity of time between depositing the foam layer and applying a top application surface on the foam layer, among other data that can be collected during the application of the foam layer.

[0097] The device 901 includes instructions 993 stored by the machine readable medium 980 that is executed by the processor resource 981 to provide the production analysis data to a machine learning model to compare the production analysis data to threshold data of the machine learning model. In these embodiments, the machine learning model utilizes production data and quality data from a plurality of different production sites that produce a product that includes the application surface 934 and foam layer on the application surface 934. In some embodiments, the machine learning model can correlate the production analysis data with a plurality of quality data associated with a product that includes the application surface 934. As described herein, the plurality of production data and/or production analysis data can be correlated with a plurality of quality data. In this way, the production data can be combined with the quality data such that the specific quality data of a particular product can be utilized with production data of the particular product. The production data and quality data can be correlated under a particular product identifier to associate the specific product with the production data and quality data.

[0098] The device 901 includes instructions 994 stored by the machine readable medium 980 that is executed by the processor resource 981 to identify when production data of the production analysis data is outside a threshold range of production data identified by the machine learning model. As described herein, the production data can be monitored in real time and during a time period that may not be possible without imaging devices such as imaging device 912. For example, the surface area with an applied foam material layer can be transported to have additional layers deposited or attached such that the additional layer is applied within a threshold quantity of time. In this way, monitoring production data utilizing the machine learning model can prevent a product from being delivered to a customer.

[0099] As described herein, the plurality of production data and the plurality of quality data can be provided to the machine learning model as production analysis data. The production analysis data can be utilized as federated data for a plurality of different production sites. The plurality of production data and the plurality of quality data provided to the machine learning model can lack raw data (e.g., does not include original data, etc.) collected by the imaging device 912. As used herein, raw data refers to data collected during the production process. The production data, quality data, and/or production analysis data may not include the actual data collected, but instead include calculations utilizing the actual data collected. In this way, a higher level of security is provided to the plurality of production sites. The plurality of production data and the plurality of quality data can be provided to the machine learning model to train the machine learning model.

[00100] The device 901 includes instructions 995 stored by the machine readable medium 980 that is executed by the processor resource 981 to generate a notification to alter a production setting of the application of the foam layer based on the identified production data. As described herein, the device 901 can generate a notification that a setting of the application of the foam layer was outside a particular production data and may be defective. In some embodiments, the device 901 can identify the produced product or portion of the produced product as defective and send a notification that the produced product or portion of the produced product is defective. In some cases, the identified product can be prevented from shipment or taken out of production of further products.

[00101] The device 901 includes instructions stored by the machine readable medium 980 that is executed by the processor resource 981 to receive a product review, from the machine learning model, that includes alterations to applying the foam layer to the application surface to alter the production data and increase the quality level of the product that includes the quality level. The product review can include an analysis of the quality data

and production data for a specific product or range of products. The product review can include an analysis of an expected quality of the product based on the production data for the specific product. In other embodiments, the product review can include a cause of an identified failure of the product based on the production data. In this way, the product review can compare the production data of the product to the production data and quality data of different products.

[00102] The device 901 can include instructions stored by the machine readable medium 980 that is executed by the processor resource 981 to provide the plurality of production data and the plurality of quality data to update a machine learning model associated with the product that includes the application surface 934. In these embodiments, the machine learning model can utilize production data and quality data from a plurality of different production sites that produce the product that includes the application surface 934 and the foam layer. In other embodiments, the device 901 can provide a product review request to the machine learning model for the product that includes a quality level. As described herein, a product review request can be a request to analyze a cause of an identified failure. However, the product review request can be a request to analyze a particular product or range of products to determine if the product or range of products were manufactured within a current set of production ranges determined by the machine learning model.

[00103] The device 901 can include instructions stored by the machine readable medium 980 that is executed by the processor resource 981 to receive a plurality of threshold ranges based on the plurality of production data and the plurality of quality data provided by a plurality of different production sites. As described herein, the plurality of threshold data can include a threshold range that can be applied to a plurality of production data during production of the product. The plurality of threshold ranges can be updated or altered at one or more of the plurality of different production sites to increase a quality data of the product produced. In a specific example, the plurality of threshold ranges can include, but are not limited to: a temperature threshold, environmental thresholds, a gel-time threshold, a contact-time threshold, a bubbling threshold, among other thresholds.

[00104] The device 901 can include instructions stored by the machine readable medium 980 that is executed by the processor resource 981 to monitor received image data of the application during the application of the foam layer on the application surface 934 at the production site. As described herein, the imaging device 912 can be utilized to monitor the production data in real time during production of products. In these examples, the device 901 can monitor production data of the foam layer based on the received image data. Monitoring

the production data can include comparing the production data to production thresholds identified by the machine learning model.

[00105] The device 901 can monitor environmental data of the production site during the application of the foam layer, and generate a notification when the production data or the environmental data are outside the threshold ranges provided by the machine learning model. As described herein, the edge computing device for the production site can generate notifications when the environmental data or production data are outside a threshold range identified by the machine learning model. The device 901 can generate a notification when a combination of environmental data and production data are outside a combined threshold range. For example, the environmental data of exterior temperature can exceed a particular threshold that changes the threshold for curing time or gel-time of the foam later. In this example, the combination of the environmental data with a particular curing time or gel-time can exceed a combined threshold for an environmental data and production data. Other combinations of environmental data and production data can be utilized to generate notifications.

[00106] The device 901 can include instructions stored by the machine readable medium 980 that is executed by the processor resource 981 to receive a set of federated data instructions from the machine learning model that indicates parameters for calculating the plurality of production data and collecting the image data. The set of federated instructions can be instructions from the machine learning model regarding how to generate federated data that can be provided to the machine learning model. As described herein, the product analysis data can be received from a plurality of production sites that each generate the production analysis data according to specifications from the machine learning model. In this way, the data can be collected and compared using the machine learning model. In addition, the collected data can protect privacy rights of the production site that is providing the data.

[00107] In this way the federated data instructions can include instructions on how to set up the imaging device 912 such that a similar portion of an application surface 934 is captured by the plurality of different production sites. In a similar way, the lighting or other settings of capturing the data can be standardized across the plurality of different production sites. The calculation for determining the production data and/or the quality data can be standardized across the plurality of different production sites through the federated data instructions. In these embodiments, the set of federated data instructions include instructions for positioning the imaging device 912 relative to the application surface 934 and positioning a light source relative to the application surface 934. Other types of federated instructions can

be provided to different production sites to ensure that the data collected and provided to the machine learning model is standardized.

[00108] Although specific embodiments have been described above, these embodiments are not intended to limit the scope of the present disclosure, even where only a single embodiment is described with respect to a particular feature. Examples of features provided in the disclosure are intended to be illustrative rather than restrictive unless stated otherwise. The above description is intended to cover such alternatives, modifications, and equivalents as would be apparent to a person skilled in the art having the benefit of this disclosure.

[00109] The scope of the present disclosure includes any feature or combination of features disclosed herein (either explicitly or implicitly), or any generalization thereof, whether or not it mitigates any or all of the problems addressed herein. Various advantages of the present disclosure have been described herein, but embodiments may provide some, all, or none of such advantages, or may provide other advantages.

[00110] In the foregoing Detailed Description, some features are grouped together in a single embodiment for the purpose of streamlining the disclosure. This method of disclosure is not to be interpreted as reflecting an intention that the disclosed embodiments of the present disclosure have to use more features than are expressly recited in each claim. Rather, as the following claims reflect, inventive subject matter lies in less than all features of a single disclosed embodiment. Thus, the following claims are hereby incorporated into the Detailed Description, with each claim standing on its own as a separate embodiment.

Claims

What is claimed is:

1. A method, comprising:
 - receiving a review request for a product that includes an identified failure related to a foam material of the product;
 - identifying production analysis data associated with a production process for applying the foam material to the product, wherein the production analysis data includes data captured during production of the product;
 - providing the production analysis data for the product to a machine learning model for producing the product to compare the production analysis data to designated data ranges for applying the foam material to the product;
 - determining data from the production analysis data that are outside of the designated range identified by the machine learning model; and
 - identifying a cause of the identified failure during the production of the product based on the determined data.
2. The method of claim 1, further comprising training the machine learning model with production analysis data from a plurality of data sources that are associated with a plurality of different production sites that produce elements of the product or similar elements associated with the product.
3. The method of claim 2, wherein the production analysis data from the plurality of data sources includes data associated with depositing a foam material layer on an application surface.
4. The method of claim 3, wherein the production analysis data includes environmental data and process timing data associated with a time of depositing the foam material layer.
5. The method of claim 1, wherein the production analysis data for the product with a foam material layer includes foam deposition device data, foam deposition stream data, foam surface distance data, foam surface bubbling data, over-rolling data, formed foam edge data, and product dimensions data when the product includes a foam material.

6. The method of claim 1, further comprising training the machine learning model by identifying a first plurality of products that include corresponding production analysis data within a range of the production analysis data of the product as similar manufacturing condition products.
7. The method of claim 6, further comprising training the machine learning model by identifying a second plurality of products that include the identified failure as similar failed products.
8. The method of claim 7, further comprising training the machine learning model by:
 - comparing the identified failure of the product to a failure status of the first plurality of products to identify products from the first plurality of products that include a same failure type as the identified failure; and
 - comparing the production analysis data of the product to production analysis data corresponding to the second plurality of products to identify products from the second plurality of products that include production analysis data within the range of the production analysis data of the product.
9. A machine-readable medium, storing machine-readable instructions which, when executed by a processor of a device, cause the processor to:
 - train a machine learning model of a production process for applying a foam material to a type of product utilizing production analysis data captured during the production process of the type of product at a plurality of different sites, wherein the machine learning model correlates the production analysis data of applying the foam material to a quality level of the foam material for the type of product;
 - provide the production analysis data for a particular site to the machine learning model, wherein the production analysis data includes image data and environmental data during application of the foam material for the type of product at the particular site over a period of time;
 - identify data of the production analysis data for the particular site that includes a value that is outside a determined range of the machine learning model; and
 - generate a notification to alter a production setting of the production process for the particular site to change the value to be within the determined range of the machine learning model.

10. The machine-readable medium of claim 9, wherein the production setting of the production process includes at least one of:
- a type of a foam distribution device;
 - a backpressure provided by the foam distribution device;
 - a quantity of a component of the foam material;
 - a flow rate of the foam distribution device;
 - a mixture ratio of a foam material deposited by the foam distribution device;
 - a rate of an application surface moving through a distribution area of the foam distribution device;
 - a contact time between the foam material and a top application surface; and
 - an operation time duration of the foam distribution device.
11. The machine-readable medium of claim 9, wherein the production analysis data captured during the production process at the plurality of different sites includes imaging data to determine a surface texture of a foam material layer of the type of product.
12. The machine-readable medium of claim 11, wherein the production analysis data captured during the production process at the plurality of different sites includes hyperspectral imaging data to determine chemical formulation data for the foam material layer.
13. The machine-readable medium of claim 9, wherein the production analysis data captured during the production process at the plurality of different sites is federated data received from the plurality of different sites.
14. The machine-readable medium of claim 9, comprising instructions to update the machine learning model utilizing production analysis data captured at the particular site.
15. A system, comprising:
- an imaging device to capture image data of an application surface during an application of a foam layer on the application surface at a production site;
 - a device configured to:
 - monitor received image data of the application surface during the application of the foam layer on the application surface at the production site;

calculate production analysis data associated with applying the foam layer on the application surface based on the image data;

provide the production analysis data to a machine learning model to compare the production analysis data to threshold data of the machine learning model, wherein the machine learning model utilizes production data and quality data from a plurality of different production sites that produce a product that includes the application surface and foam layer on the application surface;

identify when production data of the production analysis data is outside a threshold range of production data identified by the machine learning model; and

generate a notification to alter a production setting of the application of the foam layer based on the identified production data.

16. The system of claim 15, wherein the device is to receive a set of instructions that indicates parameters for calculating the production analysis data.

17. The system of claim 16, wherein the set of instructions include instructions for positioning the imaging device relative to the application surface and positioning a light source relative to the application surface.

18. The system of claim 15, wherein the production data and the quality data provided to the machine learning model lacks raw data collected by the plurality of different production sites.

19. The system of claim 15, wherein the device is configured to receive a plurality of updated threshold data based on the production data and the quality data provided by the plurality of different production sites.

20. The system of claim 15, wherein the device is configured to:

monitor environmental data of the production site during the application of the foam layer; and

generate the notification when the environmental data are outside the threshold range provided by the machine learning model.