

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. For high index foam formulations, a primer or adhesion promoting layer is distributed over the metal facings before the polyurethane laydown. This is done through a rotating disk, which spreads droplets of the reacting primer on the application surface. The application of the adhesion promoting layer is considered mandatory when the foam in use is a high index polyisocyanurate type, but is also recommended for other polyurethane foams, since adhesion promoting layer ensures durable adhesion of the foam to the metal sheets.

[0004] Appropriate distribution of the primer 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 adhesion promoting layer application is currently poorly monitored, if at all. There is currently no quantitative check of the primer distribution 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 an adhesive promoting layer can include, but are not limited to: droplet distribution data, layer uniformity data, composition data, mixture ratio data, time data between depositing the adhesive promoting layer and depositing a subsequent layer, humidity data, and/or temperature data, among other data that can potentially affect a quality of a produced product utilizing the adhesive promoting 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 thermal image of an application surface.

[0010] Figure 3 is one example diagram illustrating identifying curing rates and mixing ratios of an adhesive promoting layer.

[0011] Figure 4 illustrates an example of a method for production analysis modeling for product quality detection.

[0012] Figure 5 illustrates an example of a machine readable medium for production analysis modeling for product quality detection.

[0013] Figure 6 illustrates an example of a device for production analysis modeling for product quality detection.

Detailed Description

[0014] 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.

[0015] 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.

[0016] 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.

[0017] 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.

[0018] 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.”

[0019] 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.

[0020] Figure 1 illustrates an example of a system 100 for production analysis modeling for product quality detection. System 100 illustrates a system for applying an adhesive promoting layer on an application surface. Although the system 100 illustrates a specific system for applying an adhesive promoting layer 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.

[0021] The system 100 includes a primer distribution device 102 that can dispense a chemical compound that is utilized as an adhesive promoting layer (e.g., primer, etc.) on a

surface. The primer distribution device 102 can include a distribution disk that can rotate to distribute the adhesive promoting layer on to a surface. The distribution disk can rotate at different speeds to spread or dispense the chemicals that comprise the adhesive promoting layer. In some examples, the adhesive promoting layer can comprise a plurality of chemicals that are distributed on to the distribution disk. In some examples, the plurality of chemicals can be distributed on the distribution disk at different flow rates to generate a particular chemical ratio between the plurality of chemicals. As used herein, a flow rate describes a rate at which a quantity of chemical is dispensed on to the distribution disk. When the primer distribution device 102 dispenses the chemical on the surface, the chemical can be dispersed in a particular droplet distribution and/or a particular layer uniformity. As used herein, the droplet distribution can be a quantity of droplets that are deposited within a plurality of sub-areas over a particular area. For example, the droplet distribution can represent a particular quantity of droplets for each of the plurality of sub-areas to identify when particular sub-areas have a relative greater or fewer quantity of drops compared to other sub-areas within the particular area.

[0022] In a similar way, the particular layer uniformity can represent a layer thickness of the adhesive promoting layer for the plurality of sub-areas over the particular area. In this way, the particular layer uniformity can identify when a first sub-area has a different layer thickness of the chemical than a second sub-area. A fluctuation of the quantity of chemical dispersed on the surface of a material can be captured and utilized as production data and/or production analysis data since the droplet distribution and/or layer uniformity can affect a quality of an end product. In some embodiments, production settings data can be included with the image data such that the productions settings utilized to produce the particular layer uniformity can be used as production analysis data.

[0023] The adhesive promoting layer on the surface can be illustrated by the surface portion 104. The surface portion 104 can be a metal surface that includes the adhesive promoting layer deposited by the primer distribution device 102. The system 100 can include a light source 110 that can be directed to the surface portion 104. The light source 110 can be a visible light source and/or other type of light source based on the type of images to be captured. The location or angle of the light source 110 can be altered over a period of time to capture a plurality of different types of images of the surface portion 104 over the period of time.

[0024] The surface portion 104 can be positioned on a transportation system to bring the surface portion 104 to a different area to allow a different substance or chemical to be

deposited on the surface portion 104. In these embodiments, the light source 110 can be positioned at first location and a different light source can be positioned at a second location. In this way, the surface portion 104 can be captured with different light sources as it moves from a location to receive a deposit from the primer distribution device 102 to a different distribution device.

[0025] Transporting the surface portion 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 portion to move from the first location to the second location. The system 100 can include additional sensors to monitor a quantity of time it takes for the surface portion 104 to move from the location to receive the chemical deposit from the primer distribution device 102 to a different distribution device. The chemical deposited by the primer distribution device 102 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 portion 104 reaches the different distribution device.

[0026] The system 100 can include an imaging device 112. The imaging device 112 can be a device to capture images of the surface portion 104 to identify properties of the adhesive promoting layer deposited on the surface portion 104 by the primer distribution device 102. 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 portion 104. 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 portion 104 at the same or similar position from the primer distribution device 102. In this way, the data captured by the imaging device 112 can be correlated to data captured at different manufacturing sites.

[0027] 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 portion 104 and/or a product utilizing the surface portion 104 can be utilized to generate production ranges that can be utilized by the system 100.

[0028] 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 portion 104. For example, humidity data, temperature data, droplet distribution data of a chemical layer, layer uniformity data of the chemical layer, and/or time data between depositing the chemical layer and depositing a different layer on the chemical layer can be correlated together and associated with a product that utilized the particular surface portion 104. In this way, a quality of the surface portion 104 can be determined over a period of time and correlated to the data associated with the surface portion 104.

[0029] 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 portion 104. 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.

[0030] 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 surface portion 104 can be discarded or not utilized in a particular product when the edge computing device 116 determines the production data 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.

[0031] As used herein, production settings can be adjustable settings that can define production parameters of how the system 100 deposits the chemical layer on the surface portion 104. For example, the production settings can include, but are not limited to: position of the imaging device 112 and/or light source 110 to alter or influence the images, the position of the primer distribution device 102, the rotational speed of the primer distribution

device 102, flow rates of the chemicals, temperature of the chemicals, temperature of the primer distribution device 102, line speed of the surface portion 104 moving from a first location to a second location to alter or influence the distribution, curing time of the chemical or primer and/or chemical ratio of the chemical or primer. In this way, the system 100 can alter or adjust the production settings to alter or adjust how the primer distribution device 102 applies the chemical layer to the surface portion 104. 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.

[0032] 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.

[0033] Figure 2 is one example diagram 230 illustrating a thermal image of an application surface. The imaging device 112 as illustrated in Figure 1 can be a thermal imaging device (e.g., infrared camera, thermographic camera, etc.). As used herein, a thermal imaging device can be a device that captures and/or displays thermal energy emitted by objects. For example, the thermal imaging device can detect and generate a visualization or image of heat signatures emitted by objects or substances. The diagram 230 can be an example of how a thermal imaging device can be utilized to determine a droplet distribution of an adhesive promoting layer on a metal surface. In other embodiments, a hyperspectral camera can be utilized to determine the droplet distribution of the adhesive promoting layer. As described further herein, a hyperspectral camera is an imaging device that captures and analyzes the electromagnetic spectrum across a range of wavelengths. That is, hyperspectral image data can be utilized to determine the droplet distribution of the adhesive promoting layer.

[0034] The diagram 230 can illustrate cold areas 232 that correspond to a metal surface or application surface and warm areas 234-1, 234-2 that correspond to the chemical of the adhesive promoting layer. In this way, a quantity and location of the warm areas 234-1, 234-2 can be utilized to identify the droplet distribution of the adhesive promoting layer. The

droplet distribution of a particular surface area can be utilized to generate production analysis data for the particular surface area. As described herein, the production settings data (e.g., settings utilized during production, etc.) can be utilized with the droplet distribution data to generate the production analysis data. As illustrated in the diagram 230, a top left quadrant of the particular surface area can include less adhesive promoting layer compared to a lower left quadrant of the particular surface area. The image captured by the thermal imaging device illustrated by the diagram 230 can be utilized to monitor the droplet distribution in real time and generate production analysis data to be provided to a machine learning model.

[0035] As described herein, the machine learning model can utilize the generated production analysis data and corresponding quality data to generate ranges for a plurality of production data. For example, the production analysis data can include the droplet distribution of the adhesive promoting layer and the machine learning model can generate a droplet distribution range for a particular manufacturing site. In this way, the particular manufacturing site can utilize the thermal imaging device to determine the droplet distribution in real time and generate notifications when the droplet distribution is outside the droplet distribution range. In addition, the machine learning model can update the droplet distribution range and/or other production data based on additional production analysis data that is received from a plurality of different manufacturing sites and/or additional quality data received from the plurality of different manufacturing sites.

[0036] The acquired images from the thermal imaging camera can be streamed to enable analysis by the machine learning model (e.g., machine learning model 114 as referenced in Figure 1, etc.). The machine learning model can verify imaging parameters, such as adhesive promoting layer distribution using imaging algorithms. The machine learning model can measure a percentage coverage measured as number of pixels with adhesive promoting layer response in contrast to metal background pixels. The image will be compared against a database of “normal” distribution images to detect anomalous distribution like uneven spread or adhesive promoting layer collection on edges. The images can be saved or stored by a database for further analysis and/or further training of the machine learning model when the percent distribution of the adhesive promoting layer is outside a threshold range for droplet distribution. The further analysis can be utilized to generate notifications for the control panel.

[0037] The production analysis data for the particular surface area can be correlated with product quality data of the particular surface area and/or product generated utilizing the particular surface area. In this way, a machine learning model can be generated and/or trained

utilizing the production analysis data and resulting product quality data for a plurality of surface areas that are generated at a plurality of different manufacturing sites. Furthermore, the machine learning model can generate production setting alterations that can be implemented by a particular site to produce production analysis data or products that implement the production analysis data associated with a relatively higher quality product.

[0038] Figure 3 is one example diagram 340 illustrating identifying curing rates and mixing ratios of an adhesive promoting layer. The diagram 340 can include graphical representations that can be a visual representation of a deposited chemical for an adhesive promoting layer generated by a hyperspectral camera. That is, curing rates and/or mixing ratios of the deposited chemical can be identified utilizing graphical representations similar to those illustrated in diagram 340 when the imaging device includes a hyperspectral camera (e.g., imaging spectrometer, etc.).

[0039] As used herein, a hyperspectral camera is an imaging device that captures and analyzes the electromagnetic spectrum across a range of wavelengths. Hyperspectral cameras can operate based on the principle of spectroscopy, which involves the analysis of light interaction with materials. These cameras use a specialized sensor capable of detecting and quantifying the intensity of light in hundreds or even thousands of spectral bands, spanning from ultraviolet (UV) to near-infrared (NIR) wavelengths.

[0040] The graph 341 can be a representation of a spectrometer graph (e.g., spectrogram, spectral graph, etc.). The graph 341 can be a visual representation of an intensity of light or electromagnetic radiation as function of a wavelength or frequency. For example, graph 341 can include a wavelength on the horizontal axis and an intensity on the vertical axis. The graph 341 can illustrate a visualization of how a machine learning model can identify a curing rate of a chemical associated with the adhesive promoting layer. The portion 342 of the graph 341 can be further analyzed by a machine learning model to determine the curing rate of a chemical over a period of time. For example, each plot of the graph 341 can correspond to a different curing time of the chemical associated with the adhesive promoting layer. The curing rate can be monitored by the machine learning model by monitoring a urethane signature growth over each of the plurality of time periods. In this way, the greater quantity of urethane can correspond to the chemical being further along in the curing process or closer to being fully cured.

[0041] The portion 342 is further magnified in graph 344. Each of the plurality of plots can correspond to the chemical at: time 0 (t-0), time 5 minutes (t-5), time 10 minutes (t-10), and/or time 2 hours (t-2hr). In this example, time 0 can be at a start time of curing and

time 2 hours can be a time 2 hours after the start time of curing. The portion 342 can illustrate a visualization of how a machine learning model can determine a curing time of the adhesive promoting layer when a second layer or additional layer is applied to the adhesive promoting layer. The curing time can be added and/or utilized as the production analysis data. The production analysis data can also include the production settings utilized when the adhesive promoting layer was applied. As described herein, the portion 342 or similar data used to generate the portion 342 can be utilized by the machine learning model to monitor the curing time of the adhesive promoting layer in real time to generate notifications when the curing time is outside a threshold curing time. In addition, the curing time can be utilized to generate the production analysis data that is provided to a machine learning model. In these examples, the curing time, production settings data, and/or environmental data can be included as the production analysis data.

[0042] The graph 345 illustrates a visualization of how a machine learning model can determine a mixing ratio of a chemical associated with the adhesive promoting layer. For example, the mixing ratio can be for a two component polyurethane adhesive. The graph 345 can be a spectrometer graph that includes the mixture compared to pure samples of the components of the mixture. The graph 345 illustrates a specific example of a mixture of isocyanate component such as Voranate™ and a polyol component such as Voramer™. However, examples herein are not so limited. Additional two component or multiple component mixtures could also utilize this type of visualization illustrated by the graph 345. For example, a two component or multiple component mixture such as epoxy could be utilized in a similar way.

[0043] The portion 346 of the graph 345 is illustrated as a magnified portion in graph 348. The graph 348 can illustrate a visualization of how a machine learning model can determine the differences between the pure samples and the mixture sample to determine the ratio of the mixture. The ratio of the mixture can alter a performance of the adhesive promoting layer. For example, the ratio of the mixture can alter a curing time of the adhesive promoting layer. In this way, the ratio of the mixture can be utilized to generate production analysis data to be provided to the machine learning model and/or utilized to monitor the ratio of the mixture in real time.

[0044] Figure 4 illustrates an example of a method 460 for production analysis modeling for product quality detection. In some examples, the method 460 can be executed by a computing device as described herein. The method 460 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.

[0045] At step 461, the method 460 can include receiving a review request for a product that includes an identified failure. 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 a 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.

[0046] 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.

[0047] At step 462, the method 460 can include identifying production analysis data associated with a production process for the product. The production analysis data includes a plurality of data captured during a production of the product. 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.

[0048] The production analysis data for the product can include, but is not limited to: droplet distribution data, layer uniformity data, 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.

[0049] 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. The production analysis data can include production analysis data of an adhesive promotion layer deposition process. Thus, the production analysis data for an adhesive promotion layer deposition process can include, but is not limited to: a mixture ratio, a curing time, a time between depositing the adhesive promotion layer and depositing a subsequent layer, a humidity, a room temperature, among other conditions that are monitored during the adhesive promotion layer deposition process.

[0050] At step 463, the method 460 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 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.

[0051] 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.

[0052] 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.

[0053] The method 460 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. 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. 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.

[0054] 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.

[0055] As described herein, the production analysis data from the plurality of data sources includes droplet distribution data and layer uniformity data when the product includes an adhesive promoting layer. The droplet distribution data and/or layer uniformity data can be utilized to determine a consistency of a particular adhesive promoting layer 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 adhesive promoting 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 adhesive promoting 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.

[0056] As described herein, the process timing data can refer to a quantity of time between depositing the adhesive promoting layer and depositing a subsequent layer. In some

examples, application of the subsequent layer can be timed to be applied during a particular stage of a curing process. As described herein, a curing time of the adhesive promoting layer 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 adhesive promoting layer was at when the subsequent layer was deposited. Thus, the process timing data can be utilized to determine the curing stage of the adhesive promoting layer.

[0057] At step 464, the method 460 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.

[0058] At step 465, the method 460 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.

[0059] Figure 5 illustrates an example of a machine readable medium 570 for production analysis modeling for product quality detection. The machine readable medium 570 can be communicatively connected to a processor resource 571 by a communication path 572. In some examples, a communication path 572 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 571 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 573, 574, 575, 576. In a specific example, the processor resource 571 utilizes a non-transitory computer-readable medium storing instructions 573,

574, 575, 576, that, when executed, cause the processor resource 571 to perform corresponding functions.

[0060] The machine readable medium 570 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 570) 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 570 may be disposed within a controller and/or computing device. In this example, the executable instructions 573, 574, 575, 576, can be “installed” on the device. Additionally, and/or alternatively, the machine readable medium 570 can be a portable, external, or remote storage medium, for example, which allows a computing system to download the instructions 573, 574, 575, 576, from the portable/external/remote storage medium. In this situation, the executable instructions may be part of an “installation package”.

[0061] The machine readable medium 570 includes instructions 573 to train a machine learning model of a production process for 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 to a quality level of the type of product. As described herein, the type of product can include an application layer or application surface that has an adhesive promoting layer applied during the production process.

[0062] The machine readable medium 570 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, 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.

[0063] 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 droplet dispersion percentage for a particular portion of a substrate as it passes from a first dispersion device to a second dispersion device. In this way, the droplet dispersion percentage 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.

[0064] The machine readable medium 570 includes instructions 574 to provide production analysis data for a particular site to the machine learning model, wherein the production analysis data includes image data and environmental data during production of 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.

[0065] The machine readable medium 570 includes instructions 575 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 droplet distribution and the layer 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 chemical layer on to 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.

[0066] 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 chemical 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.

[0067] The machine readable medium 570 includes instructions 576 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 distribution disk rotational speed, chemical temperature and flow rates, etc.) can be adjusted by the control panel or adjusted by a human user. In some examples, an adhesive promoting layer can comprise multiple chemicals that can be distributed by a rotating disk of a distribution device. The rotational speed of the rotating distribution disk can alter the droplet distribution of the adhesive promoting layer. 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 droplet dispersion percentage range and the machine learning model can indicate that a second droplet dispersion percentage range should be utilized by the particular site instead.

[0068] 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 droplet dispersion device setting can be altered to alter the droplet dispersion percentage to a value that is within the droplet dispersion percentage range of the machine learning model. Other types of settings or processes can be altered based on the cause of the identified failure.

[0069] The machine readable medium 570 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 a 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.

[0070] Figure 6 illustrates an example of a device 601 for production analysis modeling for product quality detection. In some examples, the device 601 is a computing device that includes a processor resource 671 and a machine readable medium 670 to store instructions 603, 605, 607, 609, 611 that are executed by the processor resource 671 to perform particular functions. Figure 6 illustrates how a computing device can execute instructions to perform functions described herein. The device 601 can be a machine learning model operating on a computing device.

[0071] The device 601 can be communicatively coupled to an imaging device 612 through a communication path 684. As described herein, the imaging device 612 can capture images of an application surface 604 when a chemical layer (e.g., adhesive promoting layer, etc.) is applied to the application surface 604. The captured images from the imaging device 612 can be sent to the device 601 through the communication path 684 where the captured images can be analyzed.

[0072] The device 601 includes instructions 603 stored by the machine readable medium 670 that is executed by the processor resource 671 to monitor received image data of the application surface during the application of the adhesive promoting layer on the application surface at the production site. The image data can be received from the imaging device 612 through the communication path 684. 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.).

[0073] The device 601 includes instructions 605 stored by the machine readable medium 670 that is executed by the processor resource 671 to calculate production analysis data associated with applying the adhesive promoting layer to 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 droplet distribution of a chemical layer, a layer uniformity of the chemical layer, and a quantity of time between depositing the chemical layer and depositing a different layer on the chemical layer, among other data that can be collected during the application of the adhesive promoting layer.

[0074] The device 601 includes instructions 607 stored by the machine readable medium 670 that is executed by the processor resource 671 to provide the production analysis data to a machine learning model to compare the production analysis data to threshold value ranges 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 and applied adhesive promoting layer. 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. 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.

[0075] The device 601 includes instructions 609 stored by the machine readable medium 670 that is executed by the processor resource 671 to identify when a data value 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 device such as imaging device 612. For example, the surface area with an applied adhesive promoting 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.

[0076] 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 612. 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.

[0077] The device 601 includes instructions 611 stored by the machine readable medium 670 that is executed by the processor resource 671 to generate a notification to alter a setting of the application of the adhesive promoting layer based on the identified production data. As described herein, the device 601 can generate a notification that a setting of the application of the adhesive promoting layer was outside a particular production data and may be defective. In some embodiments, the device 601 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.

[0078] The device 601 includes instructions stored by the machine readable medium 670 that is executed by the processor resource 671 to receive a product review, from the machine learning model, that includes alterations to applying the adhesive promoting 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.

[0079] The device 601 can include instructions stored by the machine readable medium 670 that is executed by the processor resource 671 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. 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. In other embodiments, the device 601 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.

[0080] The device 601 can include instructions stored by the machine readable medium 670 that is executed by the processor resource 671 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: droplet dispersion thresholds, mixture ratio thresholds, curing time thresholds, timing thresholds between different applications or operations, among other thresholds.

[0081] The device 601 can include instructions stored by the machine readable medium 670 that is executed by the processor resource 671 to monitor received image data of the application during the application of the adhesive promoting layer on the application surface at the production site. As described herein, the imaging device 612 can be utilized to monitor the production data in real time during production of products. In these examples, the device 601 can monitor production data of the adhesive promoting 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.

[0082] The device 601 can monitor environmental data of the production site during the application of the adhesive promoting 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 601 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 of the adhesive promoting later. In this example, the combination of the environmental data with a particular curing 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.

[0083] The device 601 can include instructions stored by the machine readable medium 670 that is executed by the processor resource 671 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.

[0084] In this way the federated data instructions can include instructions on how to set up the imaging device 612 such that a similar portion of an application surface 604 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 612 relative to the application surface 604 and positioning a light source relative to the application surface 604. 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.

[0085] 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.

[0086] 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.

[0087] 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;
 - identifying production analysis data associated with a production process for the product, wherein the production analysis data includes data captured during a 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 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 droplet distribution data and layer uniformity data when the product includes an adhesive promoting layer.
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 adhesive promoting layer.
5. The method of claim 1, wherein the production analysis data for the product with an adhesive promoting layer includes droplet distribution data, layer uniformity data, and environmental data at a time when the product was produced at a particular production site.

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 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 to a quality level of 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 production of 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 distribution disk position;
- a distribution disk rotational speed;
- a chemical temperature; and
- a chemical flow rate.

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 thermal imaging data or hyperspectral image data to determine a droplet distribution and a layer uniformity of a chemical 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 chemical 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 an adhesive promoting 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 adhesive promoting layer on the application surface at the production site;

- calculate production analysis data associated with applying the adhesive promoting layer to 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 applied adhesive promoting layer;

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 adhesive promoting 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 adhesive promoting layer; and
generate the notification when the environmental data are outside the threshold range provided by the machine learning model.