

WHAT IS CLAIMED IS:

1. A system for predicting and detecting of corrosion under insulation (CUI) in an infrastructure asset using machine learning and data fusion comprising:

- 5 at least one infrared camera positioned to capture thermal images of the asset;
 at least one smart mount mechanically supporting and electrically coupled to the at least one infrared camera and having a position that is adjustable with respect to the asset, the at least one smart mount including:
- 10 a communication module;
 memory storage adapted to store thermal image data received from the at least one camera;
 a battery module operative to recharge the at least one infrared camera;
 an ambient sensor module adapted to obtain ambient condition data; and
 at least one additional sensor adapted to obtain CUI-related data from the
- 15 asset;
 at least one computing device having a processor, the computing device being configured with instructions for executing a machine learning algorithm in the processor which receives input from either the communication module or memory storage of the at least one smart mount comprising: a) thermal images of the asset; b) the ambient condition data; c)
- 20 CUI-related data from the at least one additional sensor providing data fusion; and d) result data obtained from conventional CUI tests, and which outputs a CUI prediction regarding the asset; and
 a machine-learning platform adapted to train the machine learning algorithm based on accumulated input data received from the at least one computing device over time.
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2. The system of claim 1, wherein the at least one computing device is adapted to test current deployment conditions of the at least one infrared camera and at least one smart mount by executing the machine learning algorithm using current infrared images, ambient sensor data and CUI-related data by determining whether performance of the machine
- 30 learning algorithm under current deployment conditions meets a threshold level.

3. The system of claim 2, wherein the performance of the machine learning algorithm conditions is measured by at least one of:
- corrosion prediction accuracy;
 - a cost of deployment and testing; and
 - 5 a speed of deployment and testing.
4. The system of claim 2, wherein the deployment conditions tested by the at least one computing device include a time of year in which the at least one infrared camera and at least one smart mount are deployed or a time of day in which the at least one infrared camera and
- 10 at least one smart mount are deployed.
5. The system of claim 2, wherein the deployment conditions tested by the at least one computing device include a position, orientation and image capture duration of the at least one camera.
- 15 6. The system of claim 2, wherein the deployment conditions tested by the at least one computing device include a position, type and number of images captured per time period of the at least one camera.
- 20 7. The system of claim 1, wherein the at least one smart mount includes a fixture for supporting the infrared camera, the fixture being rotatable and extendable to enable the infrared camera to be translated and tilted.
8. The system of claim 1, wherein the asset includes identification tags and at least one smart
- 25 mount further includes a standard camera operative to scan the identification tags on the asset.
9. The system of claim 1, wherein the at least one additional sensor comprises a magnetic sensor.
- 30 10. The system of claim 1, further comprising a control station communicatively coupled to the at least one smart mount and adapted to transmit configuration and control commands to the at least one smart mount.

11. The system of claim 1, wherein the machine learning algorithm employed by the at least one computing device includes a deep recurrent neural network.

12. The system of claim 11, wherein the deep recurrent neural network is a long short term
5 memory (LSTM) network.

13. The system of claim 1, wherein the machine learning algorithm employed by the at least one computing device further includes a convolutional neural network.

10 14. The system of claim 1, wherein the at least one computing device is configured to perform noise reduction on the data received from the at least one smart mount.

15. The system of claim 1, wherein each of the at least one smart mounts can communicate with each other via their respective communication modules.

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16. A method of obtaining data from an infrastructure asset for enabling prediction and detection of corrosion-under-insulation (CUI) comprising:

capturing thermal image data of the asset over time;

probing the asset using an additional sensing mode to obtain additional probe over
20 time;

measuring ambient conditions to obtain ambient condition data over time;

combining the thermal image, additional probe and ambient condition data into a
computer readable file;

scanning the asset for identification tags to obtain tag photo data;

25 including the tag photo data in the computer readable file; and

transmitting the file to a computing device that uses an algorithm that uses the thermal image, additional probe and ambient condition data to predict whether the asset contains CUI.

17. The method of claim 16, wherein the additional sensing mode is based on magnetometry.

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18. The method of claim 16, wherein the ambient condition data includes temperature, humidity and air pressure measurements.

19. A method of predicting corrosion-under-insulation (CUI) in an infrastructure asset using a cloud computing platform and data fusion, comprising:

receiving a stream of data including thermal images of the asset, additional sensor probe data of the asset, and ambient conditions at the asset;

5 executing, in real time, one or more machine learning algorithms using the received stream of data and weights received as updated from the cloud computing platform to generate a prediction as to whether the asset contains CUI; and

transmitting the received stream of data and prediction to the cloud computing platform.

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20. The method of claim 19, further comprising filtering the received data for noise.

21. The method of claim 19, further comprising generating synthetic thermal image data based on ambient conditions and parameters of the asset using a thermal dynamic model.

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22. The method of claim 21, wherein, at the cloud computing platform, the synthetic thermal image data is combined with the stream of including thermal images of the asset, additional sensor probe data of the asset, and ambient conditions at the asset to create a data training set for training a machine learning model.

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23. (Original) The method of claim 22, wherein the machine learning model including a deep recurrent neural network.

24. (Original) The method of claim 23, wherein the deep recurrent neural network includes a
25 long short memory network (LSTM)

25. (Original) The method of claim 22, wherein the machine learning model further includes a convolutional neural network.

30 26. A method of optimizing deployment conditions of at least one investigative kit for obtaining data from an infrastructure asset to enable prediction and detection of corrosion-under-insulation (CUI) comprising:

receiving thermal images, sensor data acquired from asset over time acquired by the at least one investigative kit, and deployment condition information regarding the at least one investigative kit;

5 obtaining result data of conventional CUI detection methods corresponding of the asset over time;

training a machine learning algorithm using the captured thermal images and other sensor data and the result data acquired from the asset; and

testing the deployment conditions of the at least one investigative kit by:

10 receiving current test conditions including ambient condition data and current deployment conditions at the at least one investigative kit to obtain ambient condition data over time;

executing the machine learning algorithm using the ambient conditions data and current deployment conditions of the at least one investigative kit;

15 on determining whether a performance of the machine learning algorithm based on the test conditions exceeds a preset performance threshold;

if performance of the machine learning algorithm exceeds the threshold, optimizing the deployment conditions using the test conditions;

20 if performance of the machine learning algorithm does not exceed the threshold, changing the deployment conditions of the at least one investigative kit; and

iteratively repeating execution of the machine learning algorithm until performance exceeds the threshold or a set number of repetitions have been conducted.

27. The method of claim 26, further comprising measuring the performance of the machine learning algorithm based on at least one of the following:

corrosion prediction accuracy using current test conditions;

a cost of deployment and testing; and

a speed of deployment and testing.

30 28. The method of claim 26, wherein the current deployment conditions include a time of year at which the at least one investigative kit is deployed or a time of day at which the at least one investigative kit is deployed.

29. The method of claim 26, wherein the current deployment conditions tested by the at least one computing device include a position, orientation and image capture duration of the at least one investigative kit.
- 5 30. The method of claim 26, wherein the current deployment conditions tested by the at least one computing device include a position, type and number of images capture per time period of the at least one investigative kit.