CLAIMS

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

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:

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 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) CUI-related data from the at least one additional sensor; and (d) results of prior 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,

in which the inputs to the machine learning-platform comprise sensor data from at least two sources that detect CUI-related data including the at least one infrared camera and the at least one additional sensor, which combination of data from the at least two sources of sensor data provides data fusion.

2. A system according to Claim 1, in which 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 learning algorithm under current deployment conditions meets a threshold level.

3. A system according to Claim 2, in which 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

a speed of deployment and testing.

4. A system according to Claim 2, in which the current 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 at least one smart mount are deployed.

5 A system according to Claim 2, in which 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 camera.

6. A system according to Claim 2, in which the current 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.

7 A system according to Claim 1, in which 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. A system according to Claim 1, in which the at least one smart mount further includes a standard camera operative to scan the identification tags that appear on the asset.

9. A system according to Claim 1, in which the at least one additional sensor comprises a magnetic sensor.

10. A system according to 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. A system according to Claim 1, in which the deep recurrent neural network is a long short term memory (LSTM) network.

12. A system according to Claim 1, in which the at least one computing device is configured to perform noise reduction on the data received from the at least one smart mount.

13. A system according to Claim 1, in which each of the at least one smart mounts can communicate with each other via their respective communication modules.

14. A method of predicting corrosion-under-insulation (CUI) in an infrastructure asset using 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;

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

transmitting the received stream of data and prediction to the database,

in which the one or more machine learning algorithms include a supervised machine learning algorithm obtained by training at least one of a convolution neural network and a deep recurrent neural network using a training data set comprising, for a plurality of assets, (i) thermal images of each asset, (ii) additional sensor probe data of each asset, (iii) ambient conditions at each asset, and (iv) known CUI results data.

15. A method according to Claim 14, further comprising filtering the received data for noise.

16. A method according to Claim 14, further comprising generating synthetic thermal image data based on ambient conditions and parameters of the asset using a thermal dynamic model.

17. A method according to Claim 16, in which, at the database, the synthetic thermal image data is combined with the stream of data including thermal images of the asset, additional sensor probe data of the asset, and ambient conditions at the asset to create the training data set.

18. A method according to Claim 14, in which the deep recurrent neural network includes a long short memory network (LSTM).