State of Artificial Intelligence (AI) in Thermographic Non-Destructive Evaluation (NDE) and its role in NDE 4.0

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Abstract

This paper discusses the current trends and state of the art in using artificial intelligence (AI) for analyzing thermographic inspection data. Several articles aimed at automating the process of dispositioning parts/components using thermography were reviewed and presented. In addition, the challenges and path forward for achieving the deliverables of NDE 4.0 in the context of thermography were discussed and elaborated.

1. INTRODUCTION: NDE 4.0

Non-destructive evaluation (NDE) 4.0 is a phenomenon coined by NDE researchers, practitioners, and professionals following the footsteps of the fourth industrial revolution (Industry 4.0) which calls for development and integration of several emerging technologies like 5G, blockchain, cloud storage, cloud computing, artificial intelligence (AI), big data, quantum computers, and extended reality for a purpose that was not achievable previously. Although there is no standard definition for NDE 4.0, there is a consensus among the NDE community about what the NDE 4.0 phenomenon entails [1–4]. NDE 4.0 calls for development and integration of autonomous/semi-autonomous inspection technologies in an industrial workflow with feedback from findings learnt while inspecting assets (components, specimens, or parts) into the design and production processes. The technologies required to achieve this goal overlap with the technologies that must be developed/matured and integrated to achieve the goal envisioned for Industry 4.0. Traditionally, NDE has been used in the industry to ensure quality and safety. Although this approach ensures that the inspected components are following design specifications, it has not been a revenue generating part of the supply chain, unless you own/operate an NDE firm. The advent of NDE 4.0 redefines the role of NDE in the industry to not just ensure safety and quality of parts/components in a self-regulating fashion but to also use findings from inspecting these parts/components to optimize/improve design and production processes making it a revenue generating aspect of the workflow. Artificial Intelligence (AI)and machine learning are key technology areas that can drive autonomous decision making in the workflow. It is important that the NDE community embraces AI to (1) analyze inspection data, (2) disposition parts/components based on findings from the inspection data, and (3) help optimize the production processes in-line with expectations from the NDE 4.0 revolution. In this paper, a brief overview of the current state-of-the-art in AI for thermography is laid out and the path forward for this modality in the context of NDE 4.0 is discussed.

Supervised machine learning architectures have evolved exponentially in the last decade starting with the traditional fully connected neural networks (FCN), followed by shallow and deep convolutional neural networks (CNN), generative adversarial networks (GAN), physics informed neural networks (PINN), recurrent neural networks (RNN), auto encoders, transformers and other large language models. NDE researchers have leveraged almost all these architectures to improve the speed, and reliability of inspection techniques. In the next few sections, we will briefly discuss how different machine learning architectures have been leveraged in thermographic NDE.

2. INFRARED THERMOGRAPHY AND AI

Thermographic NDE of a scene/part/component can be performed in two ways (1) active, and (2) passive thermography. In active thermography, the part is heated/cooled to induce a thermal gradient using an external source like heat lamp (for example, flash thermography), induction coil(for example, induction thermography), laser, and forced air[5–7]. After inducing a thermal gradient, the changes in surface temperature of the component are monitored using an infrared camera. Defects in a part can be localized with this approach because the thermal signature of a defective portion in the component would be different compared to a defect free location. In passive thermography, no external source is required to induce a thermal gradient. The part under inspection has its own heat signature which can be captured using an infrared camera to identify defects or anomalies.

Infrared (IR) cameras are classified into three types depending on the wavelength of the IR spectrum they are sensitive to (1) short-wave (0.9-1.7 µm), (2) mid-wave (3-5 µm), and (3) long-wave (8-14 µm). Typically, mid-wave and long-wave IR cameras are used for thermographic NDE. Long-wave IR cameras are more economical compared to mid-wave IR cameras. This is because most mid-wave IR cameras consist of cryogenic coolers. The detectors (focal plane arrays) in the mid-wave cameras must be cooled to cryogenic temperatures to minimize the detector's own radiation so the detector records the radiation from the scene. Mid-wave IR cameras are more sensitive to changes in temperature and can typically reach high frame rates; on the other hand, most commercially available long-wave cameras are not as sensitive and have a fixed frame rate (typically 30 or 60 fps). Hence mid-wave IR camera are used for applications requiring high frame rates (>60 fps) and low integration times (for example, flash thermography).

Because the data available from an infrared camera are like images from a typical visual camera (for example, webcams, and machine vision cameras); classic segmentation, object detection and object tracking frameworks (with a CNN backbone) can be directly used or optimized using transfer learning to identify anomalies. However, unlike visible light images, infrared images collected during thermographic inspections are sensitive to indications like delaminations, and sub-surface cracking that don't manifest on the surface of the component. In an industrial setup, both thermal images and visible light images can be used in tandem to autonomously disposition parts or provide an operator with initial assessment using AI and machine learning so the operator can disposition part. This advantage makes thermographic NDE an attractive modality to spearhead the NDE 4.0 campaign.

Unlike point based inspection modalities like ultrasound (UT), and eddy current (EC); thermographic NDE covers a broad area of the component at once hence reducing the time involved in collecting inspection data.

2.1 Current state of the art in application of AI for thermography

Many researchers have explored the applicability of supervised machine learning frameworks to analyze thermography data. Yang et al. [8]annotated 3000 thermal images of steel plates with locations of surface breaking and sub surface cracks. A region proposal network (RPN), and a Faster R-CNN[9] network were trained to detect the presence of surface breaking and non-surface breaking cracks using thermal images collected by heating the surface of steel plate with a rolling heater. Jang et al. [10] generated hybrid images of concrete surfaces by fusing images from a traditional optical/visual camera and thermal images from an IR camera. A GoogLeNet architecture[11] was retrained via transfer learning using about 20,000 annotated images. The trained network was able to identify micro- and macro-cracks with low false positives. Jaeger et al. [12] retrained several CNN architectures (pretrained on the ImageNet dataset) to identify cracks in turbine blades. Turbine blades were excited using an induction heater and the surface temperature was monitored using an IR camera. Each CNN architecture was trained on approximately 590 thermal images (540 with crack and 50 without crack) to detect cracks. Liu et al. [13] like [12] trained several CNN frameworks to predict crack locations in asphalt pavements. Three types of images were used to train the CNN networks (1) visible light images, (2) thermal images, and (3) fusion image obtained by combining the visible and thermal images. The networks were both trained from scratch and using pretrained weights obtained from the ImageNet dataset. It was observed that, when CNN architectures were trained from scratch, using fusion images resulted in better accuracy compared to raw visible light and thermal images. However, when pretrained CNN architectures were used to retrain for this task using transfer learning, traditional visible light images outperformed thermal and fusion images. Buongiorono et al. [14] trained different machine learning frameworks like Support vector machine (SVM), nearest neighbor clustering, and CNNs to predict if a weld was defective or healthy using thermal images/video collected during the welding process. For training each of these models, approximately 2300 thermal images were collected during welding without an external heat source. Thermal gradient induced in the parts by the process of welding was sufficient for the inspection. Each image was annotated by an operator as ‘defective’ or ‘healthy’ by analyzing electrical properties of the weld using a high precision milliohmmeter. The CNN architecture trained on this data could predict a damaged weld with close to 99% accuracy.

Ma et al. [15] developed a thermal imaging technique to detect gas leak using a wide-band thermal camera and auxiliary excitation like an external heat pulse. SVM was used to predict the presence or absence of a gas leak. The model was able to predict gas leaks with 94% accuracy. Wang et al. [16] trained 2-, 3-dimensional CNN, and a long short term memory (LSTM) model to predict gas leakage using passive IR images/videos recorded by an IR camera. Approximately 700,000 images (with and without gas leaks) were recorded and annotated to train the deep learning models. 2-D CNN networks were trained using individual images whereas 3-D CNN networks were trained using consecutive frames captured in a thermal video. It was observed that the prediction accuracy (presence/absence of gas leak) was close to 100% for the 3-D CNN networks.

Ren et al. [17] developed a super-resolution network model to reconstruct thermal images with better subject definition by leveraging both visible light and thermal images from an IR camera. The proposed CNN framework consisted of a feature extraction block, information extraction block and reconstruction module to obtain a thermal image with better edge and texture features compared to the input thermal image.

Wei et al. [18] developed a polyvinyl chloride (PVC)-Infrared dataset which consists of pulsed thermography data collected on PVC blocks with indications/holes at different locations with different sizes and depths. This work was aimed at (1) generating an open-source dataset for thermographic NDE that can be leveraged by other researchers, and (2) to demonstrate the ability of CNN frameworks to detect indications using flash/pulsed thermography. Different CNN frameworks like VGG-Net [19] and U-Net [20] were trained on this dataset to accurately identify the location of anomalies. Like Wei et al. [18], Fang et al. [21] developed a flash/pulsed thermography dataset only this dataset consists of synthetic thermography data from finite element simulations in addition to experimental data. CNN architectures like Mask-RCNN were trained to detect anomalies in this work

Unlike the previously described applications of AI in thermography where IR data are typically only considered like visible light images where we can visualize damage by physically looking at the images/videos, a sub-section of the AI community focuses on physics informed neural networks (PINN) where the optimization/loss function(s) used to train neural networks consists of the partial differential equations (PDEs) and boundary conditions (BCs) that govern the underlying physics. Lim et al. [22] used a physics informed loss consisting of the 3-D heat diffusion equation and boundary conditions while training the NN to predict the presence of defects from pulsed thermography data collected from a carbon fiber reinforced polymer sample. Limited articles are available in the literature that address using PINNs to solve thermographic NDE problems. This sub-section of AI must be explored in the context of thermography because, (1) the PDEs governing heat transfer are well defined, (2) considering them while training the NN will help address boundary effects and noise resulting from a simple 1-dimensional assumption, (3) analyzing thermal images without considering the underlying physics typically results in overestimation of size of identified defects or indications.

3. CLOSING REMARKS AND THE PATH FORWARD

It is clear from the brief review of literature described in this document that NDE researchers have embraced the AI revolution and adapted it to analyze thermographic inspection data to give the modality a certain level of autonomy. Having said that, most AI work reported in the literature in the context of thermography (or any other modalities) are proof of concept studies restricted to (1) controlled laboratory environments, and/or (2) specific material properties/geometry. We still have a long way to go before this can be integrated into an industrial environment. To accomplish this, AI techniques must be (1) *accurate* in identifying defects, (2) *reliable* (few/no false positives), (3) *fast* requiring fewer computational resources, and (4) *robust* to changes in environmental and material properties of the component.

Most of the previous work focuses on using CNN architectures to analyze images (2-D CNN) and videos (3-D CNN) for detecting indications. In addition to directly inputting thermographic video to the CNN architecture, several studies used traditional dimensionality reduction/unsupervised learning methods to preprocess thermal videos which reduces the number of training examples to obtain decent accuracy without overfitting. It is however important to also develop other capabilities to address the following challenges if thermographic inspection and AI were to be integrated to an industrial workflow:

1. Limited training data: Most AI applications for thermography suffer from unavailability of training data. Researchers are only able to generate few images/videos for training AI models because thermal images must be collected in a controlled experimental environment with multiple variables like heat source, and component geometries. This is unlike visible image datasets which typically contain hundreds of thousands to a few million annotated images for training AI models to perform tasks like object detection, tracking, and segmentation. There is a need to develop/create an open-source thermography dataset with contributors from academia and industry across the globe. Availability of such dataset(s) will help NDE researchers train AI models that are robust, accurate and most importantly will make AI models more generalizable. In other words, the model can be leverage to analyze thermographic data collected on parts/components with different geometry and material properties compared to the geometry and properties of the parts used for collected the training data. Leveraging synthetic data generated using fine difference and finite element simulations will also help improve the volume of training data.
2. Considering the physics of heat transfer: Most AI applications for thermography consider infrared images collected during inspection (especially during active thermography) like

traditional visible light images. It is important to remember that data collected in this process follows the laws of heat transfer for e.g. the heat diffusion equation in the case of pulsed thermography. Augmenting this information into the loss functions while training will make the AI model robust to presence of boundaries, changing material properties and component geometries. In this regard focusing on developing PINNs to analyze thermographic data is key.

3. Low resolution of thermal images: Thermal images collected using commercially available IR cameras typically have a low resolution (less than or equal to 512x640 pixels). Such low-resolution images might limit applicability of the method especially for cases where it is important to measure the size of indications accurately. This calls for an (1) improvement in hardware capabilities (from IR camera vendors side), and (2) artificially improving the resolution, edge features and texture by fusing thermal images with visible light images.

4. References

[1] Osman A, Duan Y, Kaftandjian V. Applied Artificial Intelligence in NDE. Handbook of Nondestructive Evaluation 4.0, Springer International Publishing; 2022, p. 443–76. https://doi.org/10.1007/978-3-030-73206-6_49.

[2] Vrana J, Singh R. NDE 4.0—A Design Thinking Perspective. J NondestrEval 2021;40. https://doi.org/10.1007/s10921-020-00735-9.

[3] Meyendorf NGH, Bond LJ, Curtis-Beard J, Heilmann S, Pal S, Schallert R, et al. NDE 4.0-NDE for the 21st Century-The internet of things and cyber physical systems will revolutionize

[4] Vrana J, Meyendorf N, Ida N, Singh R. Introduction to NDE 4.0. Handbook of Nondestructive Evaluation 4.0, Springer International Publishing; 2021, p. 1–28. https://doi.org/10.1007/978-3-030-48200-8_43-2.

[5] Ahmadi S, Lecompagnon J, Hirsch PD, Burgholzer P, Jung P, Caire G, et al. Laser excited super resolution thermal imaging for nondestructive inspection of internal defects. Sci Rep 2020;10. https://doi.org/10.1038/s41598-020-77979-y.

[6] Nobile R, Saponaro A, Pirinu A. The use of induction heating for thermographic inspection of composite laminates. IOP Conf Ser Mater Sci Eng 2023;1275:012015. https://doi.org/10.1088/1757-899x/1275/1/012015.

[7] Omar MA, Zhou Y. A quantitative review of three flash thermography processing routines. Infrared Phys Technol 2008;51:300–6. https://doi.org/10.1016/j.infrared.2007.09.006.

[8] Yang J, Wang W, Lin G, Li Q, Sun Y, Sun Y. Infrared Thermal Imaging-Based Crack Detection Using Deep Learning. IEEE Access 2019;7:182060–77. https://doi.org/10.1109/ACCESS.2019.2958264.

[9] Ren S, He K, Girshick R, Sun J. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks 2015. https://arxiv.org/abs/1506.01497

[10] Jang K, Kim N, An YK. Deep learning–based autonomous concrete crack evaluation through hybrid image scanning. Struct Health Monit2019;18:1722–37. https://doi.org/10.1177/1475921718821719.

[11] Szegedy C, Liu W, Jia Y, Sermanet P, Reed S, Anguelov D, et al. Going Deeper with Convolutions 2014. https://arxiv.org/abs/1409.4842

[12] Jaeger BE, Schmid S, Grosse CU, Gögelein A, Elischberger F. Infrared Thermal Imaging-

Based Turbine Blade Crack Classification Using Deep Learning. J NondestrEval 2022;41. https://doi.org/10.1007/s10921-022-00907-9.

[13] Liu F, Liu J, Wang L. Deep learning and infrared thermography for asphalt pavement crack severity classification. AutomConstr 2022;140. https://doi.org/10.1016/j.autcon.2022.104383.

[14] Buongiorno D, Prunella M, Grossi S, Hussain SM, Rennola A, Longo N, et al. Inline Defective Laser Weld Identification by Processing Thermal Image Sequences with Machine and Deep Learning Techniques. Applied Sciences (Switzerland) 2022;12. https://doi.org/10.3390/app12136455.

[15] Ma D, Liu A, Fan Z, Wu R, Gao J, Zhao H, et al. Gas Leakage Recognition Based on Wide-Band Infrared Imaging with the Auxiliary Excitation Method and Machine Learning Model. ACS Chemical Health and Safety 2022;29:455–66. https://doi.org/10.1021/acs.chas.2c00045.

[16] Wang J, Ji J, Ravikumar AP, Savarese S, Brandt AR. VideoGasNet: Deep learning for natural gas methane leak classification using an infrared camera. Energy 2022;238. https://doi.org/10.1016/j.energy.2021.121516.

[17] Ren Z, Zhao J, Wang C, Ma X, Lou Y, Wang P. Research on Key Technologies of Super-Resolution Reconstruction of Medium and Long Wave Maritime Infrared Image. Applied Sciences (Switzerland) 2022;12. https://doi.org/10.3390/app122110871.

[18] Wei Z, Osman A, Valeske B, Maldague X. Pulsed Thermography Dataset for Training Deep Learning Models. Applied Sciences (Switzerland) 2023;13. https://doi.org/10.3390/app13052901.

[19] Ren Z, Zhao J, Wang C, Ma X, Lou Y, Wang P. Research on Key Technologies of Super-Resolution Reconstruction of Medium and Long Wave Maritime Infrared Image. Applied Sciences (Switzerland) 2022;12. https://doi.org/10.3390/app122110871.

[20] Ronneberger O, Fischer P, Brox T. U-Net: Convolutional Networks for Biomedical Image Segmentation 2015. https://arxiv.org/abs/1505.04597

[21] Fang Q, Ibarra-castanedo C, Maldague X. Automatic defects segmentation and identification by deep learning algorithm with pulsed thermography: Synthetic and experimental data. Big Data and Cognitive Computing 2021;5:1–21. https://doi.org/10.3390/BDCC5010009.

[22] Lim WH, Sfarra S, Yao Y. A Physics-Informed Neural Network Method for Defect Identification in Polymer Composites Based on Pulsed Thermography. Engineering Proceedings 2021;8. https://doi.org/10.3390/engproc2021008014.