Reinforcement Learning Based Neural Architecture Search for Flaw Detection in Intelligent Ultrasonic Imaging NDE System

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***Abstract*— Ultrasonic flaw detection has been extensively used for NDE applications because it has high inspection resolution and accuracy. Conventional ultrasonic flaw detection is more vulnerable to human errors and time-consuming as the workload increases. The artificial intelligence (AI), such as machine learning (ML) methods, automates the evaluation process and is more reliable and practical. However, modeling the ML algorithms, such as the neural networks (NN) requires substantial computational resources for training and significant effort in obtaining efficient NN architecture. In this study, we introduce a reinforcement learning (RL) based neural architecture search (NAS) framework to automatically model the optimal NN design. By using this framework, a NAS-based NN: Ultrasonic Flaws Detection NAS Neural Network: UFDNASNet, is proposed for flaws detection with high accuracy and data-efficiency. The ultrasonic datasets are processed by the NAS framework using the recurrent neural network (RNN) controller to search for the best convolutional operations. The flaw detection performance is analyzed and compared between the introduced UFDNASNet and several hand-designed deep Convolutional Neural Networks (deep-CNN) based on detection accuracy and inference data-efficiency. To evaluate the performance for defects detection, the NNs are trained with the transfer learning (TL) using the USimgAIST dataset of B-scan images representing without-defect and with-defects cases. The B-scan images were collected by using the pulsed laser ultrasonic scanning system from 17 stainless steel specimen plates with various types of flaws and some plates without any damage. Our purpose is to realize an intelligent system to detect flaws with high accuracy for data-efficient ultrasonic NDE applications.**

Keywords*— *Ultrasonic Flaw Detection, Machine Learning, Reinforcement Learning, Neural Architecture Search, Deep Convolutional Neural Networks, USimgAIST Dataset

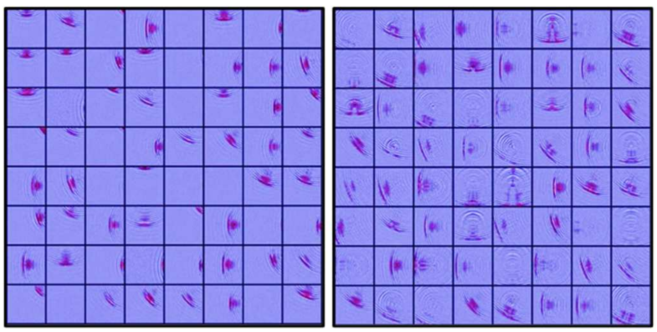
I. INTRODUCTION

In ultrasonic nondestructive evaluation (NDE), high frequency acoustic waves are used for structural health monitoring (SHM) of materials [1]. Ultrasonic detection of flaws with high scattering noise from material microstructure is challenging but can be achieved by using advanced signal processing methods [2][3]. Recently, ML is emerging in various industries to improve system performance [4]-[7]. Among ML methods, NNs have been used in NDE applications, such as flaw detection, material microstructure characterization and massive data compression [8]-[14]. In NNs, the deep Convolutional Neural Networks (deep-CNN) [15] can learn features in images with high accuracy because of the use of multiple features extraction stages. However, modeling deep-CNNs requires substantial computational resources for training and significant effort in obtaining efficient NN architecture. Therefore, in this study, we introduce a RL-based NAS framework to automatically model the optimal NN design. The NAS is a technique to automate the process to model NNs and outperforms classical NN architectures using conventional techniques. In addition, the RL is an area of ML and considers how intelligent agents react in an environment to maximize the cumulative reward. This RL-based NAS framework trains a RNN with RL to maximize the expected accuracy of the generated NN architectures on a validation set to obtain the optimal NNs [16]. By using this framework, a NAS-based NN: UFDNASNet, is proposed for flaws detection using ultrasonic images (USimgAIST dataset) [17] with high accuracy and data-efficiency. The flaw detection performance is analyzed and compared between the introduced UFDNASNet and several state-of-art hand-designed deep-CNNs based on detection accuracy and inference data-efficiency. The USimgAIST dataset of B-scan images representing without-defect and with-defects cases from 17 stainless steel specimen plates with various types of flaws. We aim to build an intelligent NDE system to detect flaws with high accuracy for data-efficient ultrasonic applications.

In this paper, Section II presents the ultrasonic USimgAIST dataset for flaw detection. Section III presents the RL-based NAS framework and NNs to detect flaws using ultrasonic images. The flaw detection performance of NNs is analyzed and compared. Section IV concludes this paper.

II. ULTRASONIC USIMGAIST DATASET FOR FLAW DETECTION

The USimgAIST dataset as shown in Figure 1 includes approximate 7000 real B-scan images representing without-defect and with-defects cases [17]. The B-scan images were collected by using the pulsed laser ultrasonic scanning system from 17 stainless steel specimen plates with various types of flaws and some plates without any damage [18]. The specimens are stainless steel plates with the thickness of 3mm. Two types of flaws: drill hole defects with diameters ϕ = 1mm, 3mm, 5mm, and slit defects with lengths l = 3mm, 5mm, 10mm, were used in these defective specimens [18]. To acquire ultrasonic images, the ultrasonic NDE system uses a pulsed laser to scan the specimen to generate ultrasonic signals and a contact transducer attached to the specimen to capture backscattered signals for flaw detection [18]. The laser scan was performed in the central region of specimens with scanning region of 100mm-by-100mm size on both front/back sides of steel plates. Then we train and deploy the neural networks to analyze ultrasonic backscattered signals in B-scan images to detect flaws. Each B-scan was normalized with the image resolution of 224 by 224 for training NNs.



a b

Figure 1. USimgAIST B-scan Images (a) Non-defective Cases, (b) Defective Cases

III. Flaw Detection Using Neural Networks

In the following sections, we introduce using the NNs to detect flaws for USimgAIST B-scan images. These B-scan images are labeled as without-defect and with-defect cases, then used to train and test the NNs. The flaw detection performance is analyzed and compared between UFDNASNet and several hand-designed deep NNs based on detection accuracy and inference data-efficiency. To improve the training performance for flaw detection, the NNs are trained with the transfer learning (TL) [19] followed by further training with ultrasonic inspection images. The TL reduces the computational cost while enhancing the classification accuracy. The inference data-efficiency is measured as the number of B-scan images processed per second on testing. In addition, the NNs were trained with 50 epochs using 5484 B-scan images for training and 1371 B-scan images for testing. The training was experimented on the Intel (R) Core (TM) i7-8750H, CPU@2.20GHz computer with NVIDIA GTX 1070 GPU 16GB RAM.

A. Flaw Detection using UFDNASNet

In this study, we introduce a RL-based NAS NN: UFDNASNet, to detect flaws using ultrasonic images. Figure 2 shows the architecture of the UFDNASNet. This NN consists of optimized combinations of *normal cell*s and *reduction cell*s [20] to extract features in ultrasonic images followed by a 2-layer fully connected NN to detect flaws. These cells were convolutional layers built using the RL-based NAS framework to optimize architecture configurations and represent the best combinations of a set of optimized convolutional operations evaluated on ImageNet [15]. The *normal cell* returns a feature map of the same dimension. The *reduction cell* returns a feature map where the width and depth are reduced by a factor of two. In this study, we use the same architecture configurations of convolutional cells as NASNet [20]. The advantages searching for the optimal architecture configurations of convolutional cells instead of the entire NN are: 1. it's much faster to only search for best cell structure; 2. these convolutional cells generalize well to other computer vision problems and are scalable to build NNs with various architectures based on different computational demands [20].

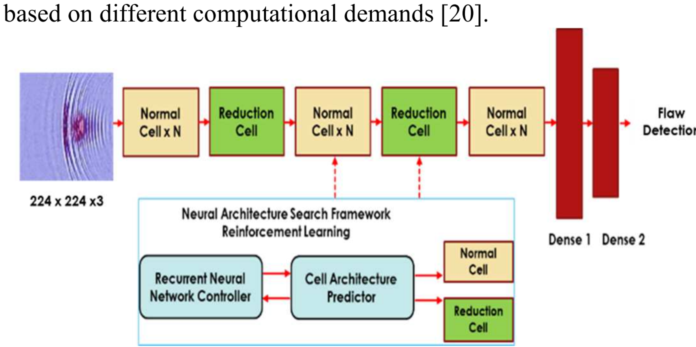


Figure 2. UFDNASNet Architecture

In the RL-based NAS framework to train the UFDNASNet as shown in Figure 3, the RNN controller samples child NN with different architectures with probabilities p by generating the model descriptions of child NNs. This RNN is trained with reinforcement learning to maximize the expected accuracy of the generated architectures on a validation set. The child NN, which is the cell architecture predictor, is trained to obtain desired validation accuracy on datasets to update the controller to generate better convolutional cell architectures over time. This validation accuracy is used as the reward signal to compute the policy gradient which is scaled by accuracy R to update the controller. Therefore, the controller will give high probabilities to child NN architectures that receive high accuracy so that the controller learns to improve its search iteratively. In training, if the convergence is satisfied, which means that the controller finds the optimal architecture of child NN, this child NN is used as the convolutional cell to build the NN with different architectures.

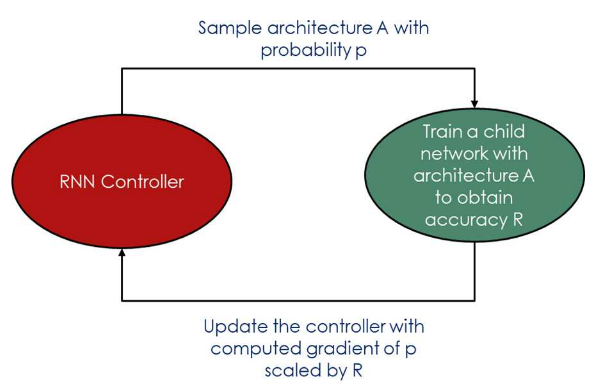


Figure 3. Reinforcement Learning based Neural Architecture Search Framework

In this study, the RL-based NAS framework was used to train the UFDNASNet to detect flaws using B-scan images and achieves 98.10% training accuracy, 96.79% testing accuracy and image processed throughput of 42 images/second to measure the inference data-efficiency to detect flaws.

B. *Flaw Detection using VGG19*

VGG19 (VGGNet) is the hand-designed deep-CNN and achieves 92.5% top-5 test accuracy in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2012 dataset [15]. This dataset includes 14 million images belonging to1000 classes. The VGG19 contains 19 weight layers and applies the same architecture pattern of convolutional layers with 3x3 kernel and 2x2 max pooling. In this study, we trained the VGG19 with the TL followed by a 2-layer fully connected NN to detect flaws using B-scan images and obtained 96.97% training accuracy, 95.77% testing accuracy and image processed throughput of 9 images/second to measure the inference data-efficiency to detect flaws.

C. *Flaw Detection using ResNet-50*

The ResNet-50 is the state-of-art deep-CNN that is hand-designed and achieves 93.0% top-5 test accuracy on the ImageNet ILSVRC dataset [15]. The ResNet-50 was proposed in 2015 by researchers who introduced a new architecture called Residual Network at Microsoft Research [15]. ResNet-50 has 50 weight layers and achieves good performance while uses less computation resources than that of VGGNet by using residual blocks. In this study, we trained the ResNet-50 with the TL followed by a 2-layer fully connected NN to detect flaws using B-scan images and obtained 97.94% training accuracy, 96.16% testing accuracy and image processed throughput of 17 images/second to measure the inference data- efficiency to detect flaws.

TABLE 1. PERFORMANCE COMPARISON USING NEURAL NETWORKS FOR FLAW DETECTION USING ULTRASONIC USIMGAIST DATASET

Model	Training Accuracy	Testing Accuracy	Inference Data-Efficiency Measurement
UFDNASNet	98.10%	96.79%	42 images/second
VGG19	96.97%	95.77%	9 images/second
ResNet-50	97.94%	96.16%	17 images/second

In Table 1, by training these NNs, we obtained the average flaw detection accuracy of 97.67% and 96.24% for training and testing respectively, to detect flaws using experimental B-scan images. In addition, we achieve the highest image processed throughput of 42 images/second using the UFDNASNet to detect flaws. The RL-based NAS NN outperforms the other hand-designed deep-NNs in terms of flaw detection accuracy and inference data-efficiency performance in this study.

IV. CONCLUSION

In this study, we introduce a reinforcement learning based neural architecture search framework to automatically model the optimal NN design. By using this framework, a NAS-based NN: UFDNASNet, is proposed for flaw detection with high accuracy and data-efficiency. The ultrasonic USimgAIST dataset of B-scan images represent without-defect and with-defect cases. The B-scan images were collected by using the pulsed laser ultrasonic scanning system from 17 stainless steel specimen plates with various types of flaws and some plates without any damage. Then the inspection ultrasonic images are processed by the NAS framework to train the recurrent neural network controller to search for the best convolutional operations. The flaw detection performance is analyzed and compared between the introduced RL-based NAS NN and several hand-designed deep-NNs based on detection accuracy and inference data-efficiency. To evaluate the performance for flaw detection, the NNs are trained with the transfer learning followed by further training with the ultrasonic images. The transfer learning reduces the computational cost while enhancing the classification accuracy. Therefore, by using these NNs, we obtained the average training accuracy of 97.67%, the average testing accuracy of 96.24%, and the highest image processed throughput of 42 images/second on testing with the UFDNASNet to detect flaws. Future work is to further enhance the flaws detection performance, such as applying innovative convolutional operations.

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