# Steel Material Microstructure Characterization using Knowledge Distillation Based Transformer Neural Networks for Data-Efficient Ultrasonic NDE System

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***Abstract*— Material microstructure characterization for texture recognition using ultrasonic testing has been widely used to examine the physical and structural integrity of materials. For system automation, Neural Network (NN) can be used to characterize the material texture accurately. However, training and deploying NNs requires substantial computational resources. In this study, we propose to use the knowledge distillation (KD) method and introduce a response-based teacher-student KD training framework to train NNs to find the optimal solution. In addition, a lightweight Ultrasonic Microstructure Characterization Transformer NN (TNN): UMCTNet, is proposed to recognize material textures using ultrasonic images. Training using the KD mechanism improves the data-efficiency of NNs by transferring knowledge from pre-trained NN models. In addition, TNN utilizes a simple network architecture with the attention mechanism resulting in reducing training and execution time. A data-efficient Ultrasonic Microstructure Characterization Convolutional NN: UMCCNet, is trained as the teacher model using ultrasonic images to distill the pre-trained knowledge into the UMCTNet with high accuracy and data-efficiency. To examine the results, an ultrasonic testbed platform was assembled, and C-scanning was created to acquire volumetric ultrasonic data from three different heat-treated steel blocks to train NNs. By applying the KD framework to train UMCTNet, we obtained the training and testing accuracy of 99.91% and 99.27% respectively, and the highest image throughput of 192 images/seconds on testing to characterize steel material microstructures.**

***Keywords*— *Data-Efficient Ultrasonic NDE System, Knowledge Distillation, Transformer Neural Network, Convolutional Neural Network, Microstructure Characterization***

## I. Introduction

Ultrasonic nondestructive evaluation (NDE) of materials for microstructure characterization has been extensively used because of high inspection accuracy [1]. Approximating the grain size using ultrasonic backscattered signals is challenging but can be used to characterize the microstructure of steel materials [2]. The intensity of ultrasonic backscattered signals is the non-explicit function of the average grain size and random distribution of grains [2]. The Rayleigh scattering region [3] where the wavelength of ultrasonic signals is larger than the average grain size is applied to acquire ultrasonic signals. Rayleigh region reveals the most sensitivity to frequency and grain size distribution [3] to better characterize material microstructure.

For system automation, machine learning (ML), such as NNs, have been used to enhance system performance in NDE industries [4]-[9]. In ultrasonic NDE, NNs have been applied for grain size estimation to characterize material microstructure [10][11], flaws detection [12] and massive ultrasonic data compression [13][14]. Among these NNs, the deep Convolutional Neural Networks (deep-CNN) can characterize steel material microstructure with high accuracy but suffer substantial computational cost for training and deployment [9][15]. This limits the performance of ultrasonic applications, specifically in the computational constraint or real-time evaluation environment. In our previous research, we have developed deep-CNNs and the Transformer Neural Network (TNN) to estimate grain size for material microstructure characterization with high accuracy and data-efficiency [9][11]. The TNN utilizes the multi-head attention mechanism [16] to replace the convolutions and recurrence entirely to learn backscattering features in ultrasonic images. And this attention mechanism largely reduces the demand for computational resources resulting in reduction in training and deployment time [16]. In this study, to further enhance the characterization performance, we introduce a response-based teacher-student KD training framework [17] to find the optimal solution. Training using the KD mechanism improves the training performance of NNs by transferring knowledge from a large heavy model to one smaller model which can be practically deployed under real-world constraints. In addition, a lightweight TNN: UMCTNet, is proposed as the student model to characterize material microstructure using ultrasonic images with high data-efficiency. By using this KD framework, a deep-CNN: UMCCNet, is trained as the teacher model using ultrasonic images to distill the pre-trained knowledge into the UMCTNet with high accuracy and data-efficiency.

To examine the results, an ultrasonic testbed platform was assembled, and C-scanning was created to acquire volumetric ultrasonic data from three heat-treated steel blocks with different grain size. The volumetric data consists of a sequence of ultrasonic backscattering images to train NNs. We aim to realize a data-efficient ultrasonic system to automatically characterize steel material microstructure with high accuracy for ultrasonic NDE applications.

In this paper, Section II presents the data-efficient ultrasonic NDE system in the laboratory and testing arrangement for data acquisition. Section III presents the KD framework used to train TNN to characterize steel material microstructure. The characterization performance of UMCCNet (teacher model), UMCTNet (student model) and distillation-UMCTNet (distillation model) is analyzed and compared. Section IV concludes this paper.

## II. Experimental Setup

Figure 1 shows the ultrasonic testbed platform for data acquisition. This platform consists of a water tank mounted with two stepper motors to automatically move the ultrasonic transducer along two directions for ultrasonic testing. A Panametrics Model 5052PR ultrasonic pulser receiver is used as the signal generator and echo receiver. And a high frequency digitizer, the Keysight MSOX2024A oscilloscope, is used to synchronize the acquired signals and monitor the ultrasonic testing. Then the ultrasonic signals are processed by the intelligent material microstructure characterization unit to recognize steel material textures with different grain sizes. A 2D C-scan path is created with 200×200 measurements (each measurement includes 7680 ultrasonic backscattered signals) to obtain ultrasonic images. In this study, three heat-treated steel blocks with different grain sizes of 14 (Grain14), 24 (Grain24), and 50 (Grain50) microns are used as specimens for ultrasonic testing. We collected 4800 ultrasonic images for each steel block specimen to train NNs.

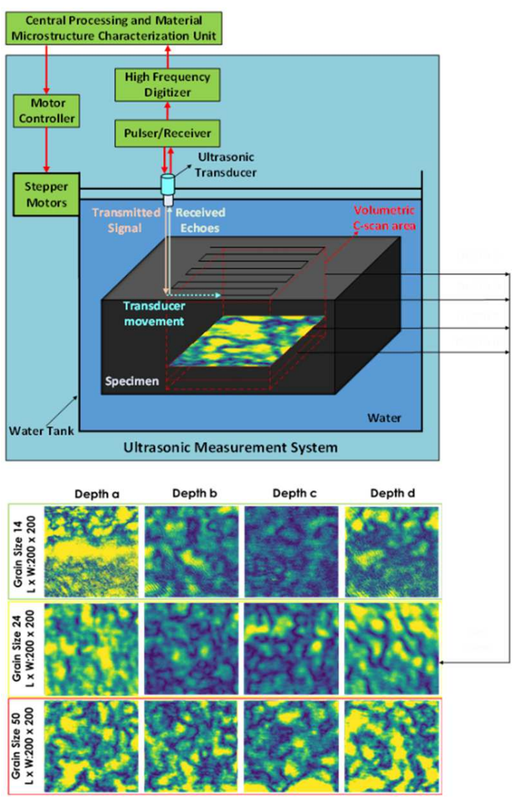


Figure 1. Data-Efficient Ultrasonic NDE System and Testing Arrangement for Data Acquisition

## III. Steel Material Microstructure Characterization Using Knowledge Distillation based Transformer Neural Network

In the following subsections, we introduce the KD framework to train TNN to characterize material microstructure for Grain14, Grain24, and Grain50 steel blocks. The experimental ultrasonic images are labeled and used to train the NNs. The characterization performance is benchmarked using the training accuracy, testing accuracy, and data-efficiency. The data-efficiency measures the NN inference performance and is calculated by the image processed throughput on testing. The image processed throughput is the number of ultrasonic images assessed per second. To enhance the characterization performance, we use transfer learning (TL) [18] to pre-train the teacher model on large datasets (ImageNet) followed by further training with experimental ultrasonic images. The NNs were trained with 50 epochs using 80% and 20% of ultrasonic images for training and testing correspondingly. The training and testing were conducted on the Intel (R) Core (TM) i7-8750H, CPU@2.20GHz computer with NVIDIA GTX 1070 GPU 16GB RAM.

### A. *Teacher Student Knowledge Distillation Training Framework*

Training using the KD mechanism improves the data-efficiency of NNs by transferring knowledge from pre-trained NN models [17]. In this KD training framework as shown in Figure 2, the teacher NN has powerful learning ability but suffers large amounts of parameters which requires extensive computational resources for training and deployment. The student NN aims to be compressed with high data-efficiency by using this KD framework to further enhance the characterization accuracy. In training, the teacher NN was pre-trained with experimental ultrasonic images with high accuracy. Then by using the KD framework, the pre-trained teacher model distills the learned features from ultrasonic images as knowledge along with ultrasonic images to train the student model. Therefore, the KD training framework improves the characterization accuracy of the student model with high data-efficiency.

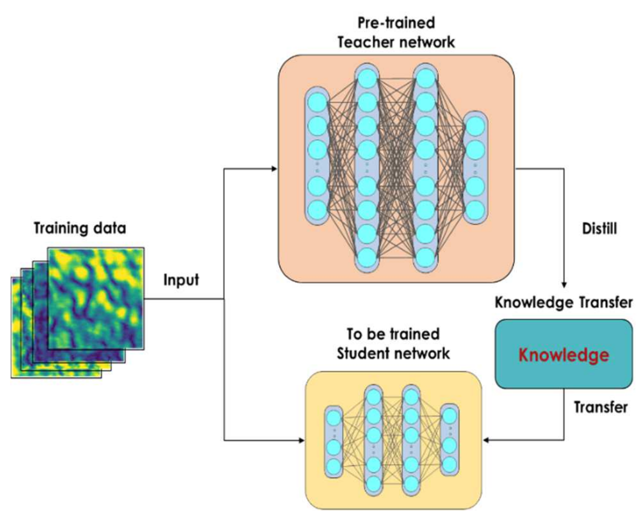


Figure 2. Teacher Student Knowledge Distillation Training Framework

### B. *Ultrasonic Microstructure Characterization Transformer Neural Network: UMCTNet*

For the student NN, we introduce a lightweight transformer NN: UMCTNet, to characterize steel material microstructure using ultrasonic images. In our previous research, we trained the Data-Efficient Ultrasonic Texture Recognition transformer NN: DEUTR transformer [19] to learn material textures using ultrasonic images with high accuracy and data-efficiency. In this study, we further improve the data-efficiency of NN with the KD based UMCTNet (distillation-UMCTNet). In training, each ultrasonic image is divided into a sequence of image patches which are linearly embedded into lower dimensions with principal features. Then these embedded features are fed as inputs to train transformer encoders [11] to characterize material microstructure. Each transformer encoder is optimized with the multi-head attention to parallelize the training process. This attention mechanism reduces the computational cost and enhances the data-efficiency of NN. Next, the residual connection [11] and layer normalization [11] are applied in each transformer encoder to further optimize the learning performance. For performance comparison, we trained the UMCTNet without using the KD training framework and obtained 99.40% training accuracy and 95.92% testing accuracy to characterize the Grain14, Grain24 and Grain50 steel blocks, and the highest image processed throughput of 192 images/second on testing this neural network.

### C. *Ultrasonic Microstructure Characterization Convolutional Neural Network: UMCCNet*

In this study, we propose a data-efficient deep convolutional NN: UMCCNet, as the teacher model. This UMCCNet can be fast trained with further improvement for material characterization from our previous research [19]. We use transfer learning (TL) [18] to pre-train the teacher NN on large datasets (ImageNet) followed by further training with experimental ultrasonic images. The TL reduces the computational cost while improving the characterization accuracy. The UMCCNet is optimized with the depthwise separable convolution architecture as the MobileNet [20]. The depthwise separable convolution block reduces the model complexity and computational cost greatly by dividing one full (spatial) convolution into the depthwise convolution and pointwise convolution [20]. And this reduces a large amount of multiplication operations. By training the UMCCNet, we obtained 99.97% training accuracy and 99.39% testing accuracy to characterize the Grain14, Grain24 and Grain50 steel blocks, and the image processed throughput of 56 images/second on testing this neural network.

Table 1 below shows the results by training the student NN using the KD training framework: distillation-UMCTNet, to characterize material textures of Grain14, Grain24, and Grain50 steel blocks. We benchmarked results based on training accuracy, testing accuracy and image processed throughput on testing to measure the data-efficiency of NNs. In Table 1, as we can see that the distillation-UMCTNet achieves 99.91% training accuracy and 99.27% testing accuracy to characterize the Grain14, Grain24 and Grain50 steel blocks with the highest image processed throughput of 192 images/second on testing this NN. Therefore, the KD training framework enhances the characterization accuracy of the student NN (UMCTNet) while enabling the fast deployment of NN, which is almost 4 times more data-efficient than the teacher NN in this study.

TABLE 1. PERFORMANCE COMPARISON USING KNOWLEDGE DISTILLATION BASED TRANSFORMER NEURAL NETWORKS FOR MATERIAL MICROSTRUCTURE CHARACTERIZATION

| Model | Training Accuracy | Testing Accuracy | Image Processed Throughput |
|---|---|---|---|
| UMCCNet (Teacher) | 99.97% | 99.39% | 56 images/second |
| UMCTNet (Student) | 99.40% | 95.92% | 192 images/second |
| Distillation-UMCTNet | 99.91% | 99.27% | 192 images/second |

## IV. CONCLUSION

In this study, we introduce a response-based teacher-student KD training framework to train NNs to characterize material microstructure from three different heat-treated steel blocks. Training using the KD mechanism improves the data-efficiency of NNs by transferring knowledge from pre-trained NN models. By using this framework, we can train and deploy data-efficient NNs with high accuracy for high-performance computational ultrasonic NDE system, specifically in the computational constraint or real-time evaluation environment. In addition, a lightweight transformer NN: UMCTNet, is proposed as the student model to learn material textures using ultrasonic images with high accuracy. For the teacher model, we trained a data-efficient deep-CNN: UMCCNet to distill the pre-trained knowledge into the UMCTNet with high accuracy. To examine the results, an ultrasonic testbed platform was assembled, and C-scanning was created to acquire volumetric ultrasonic data from steel blocks with different grain sizes to train NNs. By using the KD framework to train the distillation-UMCTNet, we obtain 99.91% training accuracy and 99.27% testing accuracy to characterize the Grain14, Grain24 and Grain50 steel blocks with the highest image processed throughput of 192 images/second on testing. This distillation-UMCTNet achieves the same characterization accuracy as the teacher NN while is almost 4 times more data-efficient than the teacher model in this study. Future work will include improving the KD training framework, exploring innovative NNs to enhance the characterization performance of the teacher and student models.

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