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Multi-Class Classification of Defect Types in Ultrasonic NDT Signals with Convolutional Neural Networks

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***Abstract*—The key objective of this work has been to detect and classify different types of flaws encountered in ultrasonic Non-Destructive Testing (NDT) applications. The flaws that are examined for classification are Side Drilled Hole, Flat Bottom Hole, and Rectangular voids with different aspect ratios. Manual inspection of ultrasonic images is often inadequate for classification purposes since it is difficult to visually discriminate the flaws due to their similarities. In particular, voids and holes closer to the edge boundaries (i.e. front or bottom of the structure) make this task especially challenging. We propose to use deep-learning methods to automate the ultrasonic flaw classification. In the proposed setup, the specimen under test is a steel block and immersion based ultrasonic testing has been considered. OnScale multiphysics simulation software has been used for data synthesis and a Convolutional Neural Network based deep learning method has been developed to classify the flaws with one hot encoding method. Preliminary results have been promising with the average classification accuracy of 90%, 93%, 95% and 91% for flat bottom hole, rectangular void with greater width, side drilled hole and rectangular void with greater length, respectively.**

***Key Words*—NDE, Ultrasound, Flaw detection, Deep learning, Convolutional Neural Networks, One Hot Encoding, ADAM optimizer,**

I. Introduction

Classification of flaws and material characterization have been been conducted using traditional signal and image processing techniques, as can be seen in [1], [2] and [3]. However, the advent of Industry 4.0 has called for integration of various technologies such as Internet of Things (IoT) and Artificial Intelligence(AI) / Data sciences [4], [5]. In this regard, it is essential to integrate smart algorithms that can help in achieving automation for detection of flaws or locating voids/holes. For example, the latter case is particularly crucial for assembling two components that need to be precisely positioned into the grooves. Our earlier work on binary classification of ultrasonic flaws have introduced multiple machine learning and deep learning algorithms [6], [7], [8] and [9]. These algorithms range from a linear classifier such as Support Vector Machines [6] to deep learning networks based on Le-Net architecture [9]. While flaw detection performance goals have been met with these proposed methods, classification of flaw types present a more complex task and may require a different approach. Several research initiatives have been carried out already for automation of defect classification using shallow learning techniques [10], [11], [12]. In this study, we aim to introduce a new deep learning network for ultrasonic flaw classification. A convolutional neural network (CNN) is proposed since it has been shown to work on ultrasonic images with minimum feature analysis or feature extraction needed [9].

Organization of this paper is as follows: The details of the data synthesis with OnScale software tool, testing setup and B-scan intensity images are presented in Section II. Section III introduces the new CNN architecture used in this work. System validation and testing results with preliminary data are discussed in Section IV and Section V.

II. Ultrasonic Data Synthesis

An immersion test setup with a specific type of void has been simulated for this work as shown in Fig. 1. In Fig. 1, the immersion liquid used is water and the metal block under inspection is steel with a Side Drilled Hole. The transducer is a sensor array operating at central frequency of 5 MHz. All data synthesis have been performed using OnScale software tools [13].

The voids that are being classified are listed below:

- Side Drilled Hole (SDH).
- Flat Bottom Hole (FBH).
- Rectangular Void with length greater than width (RVLgW).
- Rectangular Void with width greater than length (RVWgL).

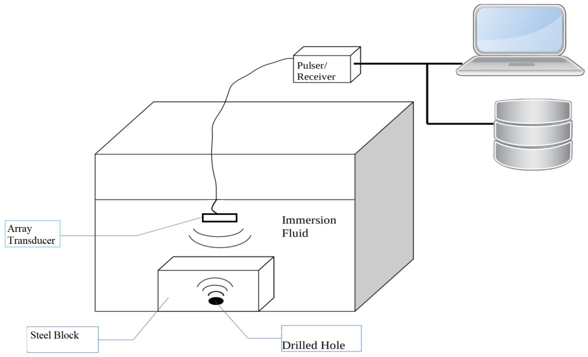

Fig. 1. Immersion setup with SDH using OnScale tools.

B-scan images corresponding to each flaw type are shown in Fig. 2. It can be seen that each flaw has distinct response but the position of the void influences the signature and it is hard to classify shapes visually. When the holes or voids are closer to the surface edges, classification task becomes further difficult.

In these experiments, the B-scan image resolution was chosen to be 427 x 1500. The x dimension represents the position of the scan and y dimension represents the time sampling. These images are fed into the neural network classifier as input features. A dataset of 400 B-scans has been created and each flaw class contain 100 samples. The resolution of B-scan images are high and has been down-sampled to 50x50 resolution which has yielded the best validation results with a training time of less than 30 seconds per epoch.

III. VHC-CNN Architecture

Several CNN architectures have been explored during the development process and the specific architecture with three ConvNet layers presented in Table I has been chosen due to its high validation accuracy. It is called Void Hole Classifier - CNN (VHC-CNN). The graphical overview of the architecture is shown in Fig. 3 and the details of the individual layers are listed in Table I. ADAM optimizer with a learning rate of 0.005 has been used. The output is chosen to be one hot encoded.

IV. Training Validation

The dataset has been split into training, validation and testing sets. The split ratio is 4:1:5 on the entire data set for the training, validation and testing, respectively. Data crunch and overfitting posed a problem but this was overcome by increasing the training and validation dataset. The existing data set was rotated 6 times at incremental steps of 30 degrees and augmented to existing dataset. Therefore, the total amount of data for training was 1120. Similar approach was adopted for validation data set. The algorithm has been implemented with Keras Python Deep Learning library [14], running on top of the TensorFlow framework and Nvidia Tesla GPUs.

Validation provides initial look at the machine learning performance after training CNN at the end of each epoch.

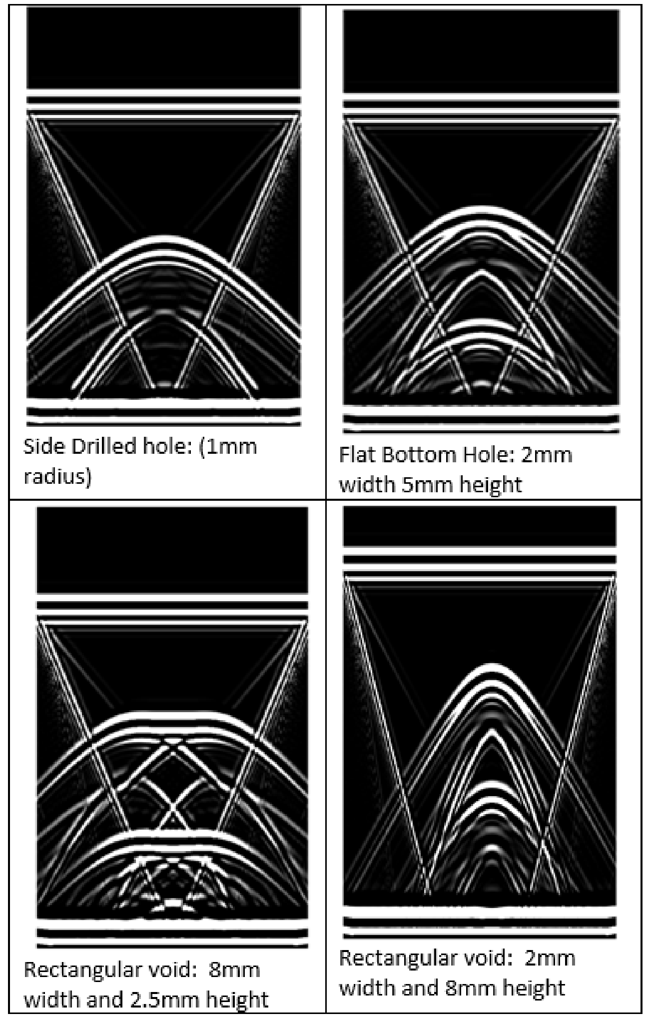

Fig. 2. B-Scan images for different flaw classes.

TABLE I
VHC-CNN Details

Layer Name	Output Size	No of Parameters
batch normalization 1	(None, 50, 50, 1)	4
conv2d 1 (Conv2D)	(None, 50, 50, 8)	208
batch normalization 2	(None, 50, 50, 8)	32
activation 1 (Activation)	(None, 50, 50, 8)	0
max pooling2d 1	(None, 25, 25, 8)	0
conv2d 2 (Conv2D)	(None, 25, 25, 16)	3216
batch normalization 2	(None, 25, 25, 16)	64
activation 2 (Activation)	(None, 25, 25, 16)	0
max pooling2d 2	(None, 12, 12, 32)	0
conv2d 3 (Conv2D)	(None, 12, 12, 32)	4640
batch normalization 3	(None, 12, 12, 32)	128
activation 3 (Activation)	(None, 12, 12, 32)	0
max pooling2d 3	(None, 6, 6, 64)	0
flatten 1 (Flatten)	(None, 1152)	0
dense 1 (Dense)	(None, 1024)	1180672
dense 2 (Dense)	(None, 128)	131200
dense 3 (Dense)	(None, 64)	8256
dense 4 (Dense)	(None, 4)	260

During training/optimization, it is critical to keep check on

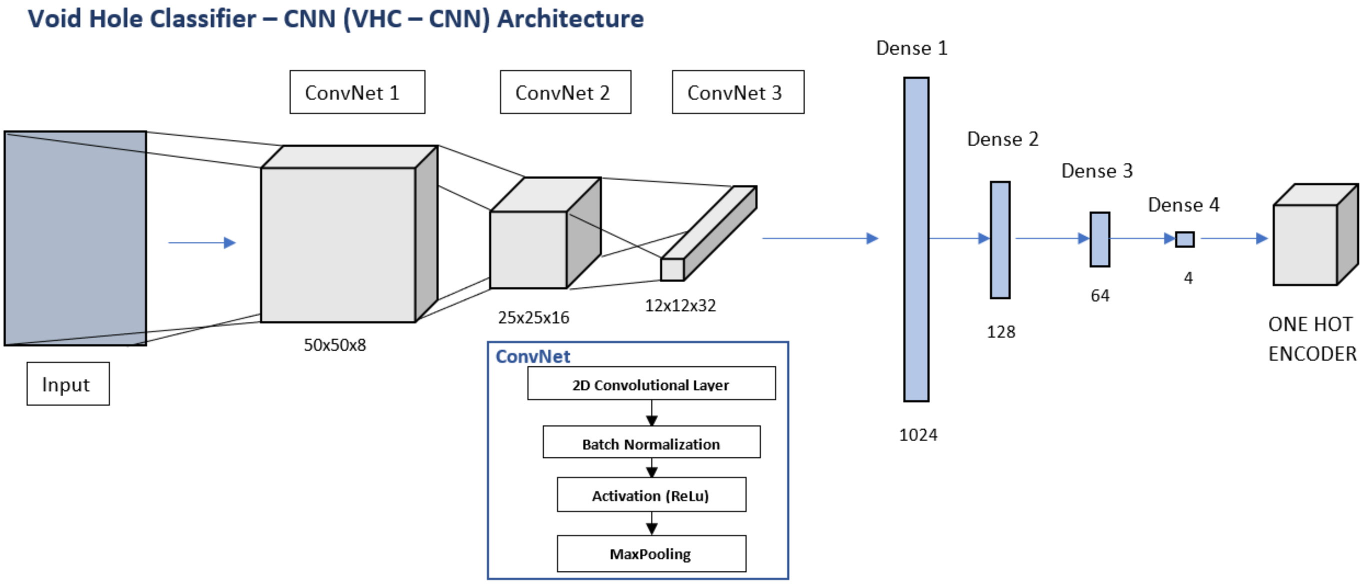

Fig. 3. VHC-CNN architecture.

the convergence and this is accomplished by checking the validation accuracy. The overall validation accuracy has been at an average of 95%. The validation accuracy for each class has been listed in the Table II.

TABLE II
VALIDATION ACCURACY

Flaw	Accuracy
FBH	92%
RVWgL	95%
SDH	97%
RVLgW	94%

It can be seen from the validation results that the side drilled hole is the easiest void type to classify, while flat bottom hole is the hardest for classification. The test results presented in the next section corroborate with the validation accuracy performance.

V. MULTI-CLASS CLASSIFICATION RESULTS

The test results for each void type have been presented in Fig. 4. They confirm the validation results. The overall average accuracy is above 90%. The miss-classification cases and performance analysis can be seen in the Table III. The table gives the entire confusion matrix. It can be seen that the highest miss-classification ratio is 5% (FBH incorrectly identified as RVLgW).

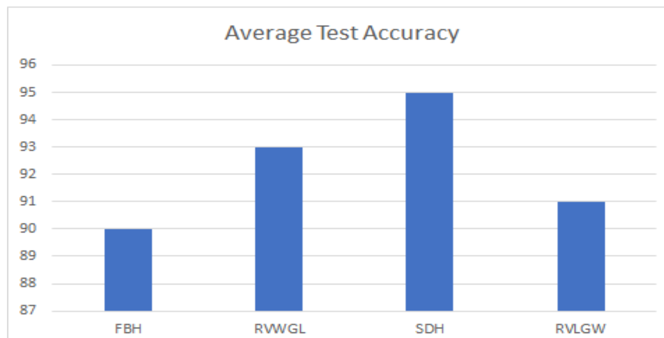

Fig. 4. Average Multi-Class Test Accuracy

TABLE III
CONFUSION MATRIX

Inference Actual Class	FBH	RVWgL	SDH	RVLgW
FBH (100 total)	90	3	2	5
RVWgL (100 total)	2	93	2	3
SDH (100 total)	2	1	95	2
RVLgW(100 total)	5	2	2	91

VI. CONCLUSION AND FUTURE WORK

This work has demonstrated that deep learning methods such as CNN can be used in Ultrasonic NDT applications wherein flaw/defect shapes need to be identified. Preliminary results show that it is harder to detect the FBH voids but this can be improved by expanding the training set by simulating a wide range of different scenarios. Another important outcome is that the proposed CNN architecture can distinguish between Flat Bottom Hole and Rectangular Voids even when they have similar dimensions (same aspect ratio). CNN was able to achieve average accuracy of above 90% in both the cases. For future work, further analysis on the proximity limit of the void or hole to the edge boundaries is necessary for enhancing the performance of VHC-CNN architecture.

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