Applications of Deep Learning

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Deep Learning based Technology for Fuel Bundle End Plate Weld Inspection

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Fuel elements welded with end plate

ABSTRACT

Detecting defects at every stage of the fabrication of nuclear fuel bundles is essential for ensuring high-quality assurance standards. This paper presents the state-of-the-art deep learning method for detecting the quality of end plate welding with each fuel element. The system can identify good and potentially incorrect welds for active assistance to operators. The proposed method achieves mean precision of 0.9918 and a mean recall of 0.9916 with test images.

KEYWORDS: *Defect identification, Welding defect, Deep learning, Visual Inspection, Quality assurance*

Introduction

The fuel bundle of Indian 540 MWe PHWR (Pressurised Heavy Water Reactor) consists of 37 cylindrical fuel elements arranged in a concentric ring of 1,6,12, and 18 configurations. A robotic system welds all the fuel elements with end plates with pre-defined welding parameters like current, time, and pressure. The robotic system then captures and displays the image of the welded assembly on a monitor (Fig.1). Visual inspection by an operator confirms the weld quality for all the pins. However, inspecting all the fuel pins requires a very high level of focus and can cause visual fatigue to operators, thus increasing the risk of the wrong inspection. Traditional machine vision methods based on feature extraction cannot meet the quality control requirements, mainly because of the variable illumination conditions and inconsistent shape and size of the defects. However, identifying surface defects from images using deep learning techniques is an active research topic [1,2,3]. One key challenge in using neural network methodology is collecting sufficient number of labeled defective samples. Further, when defective samples are insufficient, artificially generated images are needed to augment the dataset [4].

Classification of Weld

Presently, the visual acceptance criterion followed for a pin is to verify the presence of two spot weld marks on either sides of the end plate (Fig.1). Electrodes leave these marks after welding. Three categories are defined based on weld marks (Table 1).

- Normal.
- Missing spot weld marks.
- More than two spot weld marks.

Our framework checks each pin for missing or additional spot weld marks. In case of discrepancies, the operator isolates the bundle and investigates further.

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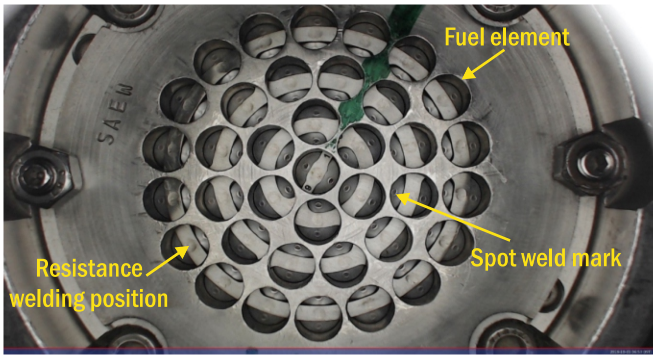


Fig.1: Fuel elements welded with end plate.

Table 1: Classification of weld quality.

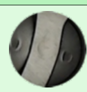
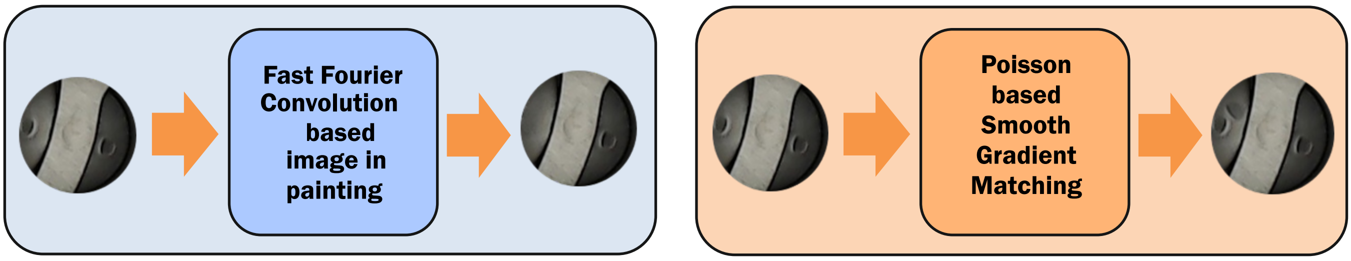
Class	Descripti on	Image	% of total images
Type - I	Normal		99.09%
Type - II	Missing spot weld mark		0.008 %
Type - III	More than two spot weld mark		0.002%

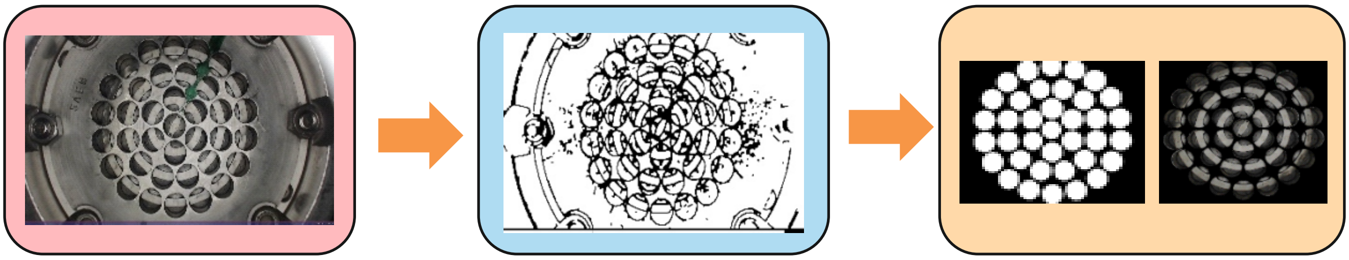
Image Dataset for Supervised Learning

An automated system captures an image of 37 fuel pins welded with an end plate after the completion of welding. Though more than 3000 bundle images are available, very few cases have pins of Type-II and Type-III (Table 1). This anomaly results in a distribution where class labels are not equal for three categories. The skewed distribution makes neural network learning algorithms less effective, especially in predicting minority class examples. Therefore, we have developed methods for the artificial generation of Type-II and Type-III cases.



(a) Artificial generation of Type II images **(b) Artificial generation of Type III images**

Fig.2: Augmentation of training dataset.



Fuel bundle with end plate **Pre-processed image after smoothening and edge detection** **Boundary masks and segmented pins of fuel bundle**

Fig.3: Generation of boundary mask and segmentation of fuel pin elements.

Artificial Generation of Type-II images

We use a method based on Fast Fourier Convolutions (FFCs) [5] for generating the images with the missing weld impressions (Type-II). Our framework selects a mask for removing the weld mark and gives it as input to FFC for processing. It does the filling, keeping the content awareness of the regions, and therefore creates smooth boundaries as if the weld was missing at that spot (Fig.2a).

Artificial Generation of Type-III images

The idea here is to crop spot weld marks from one image and clone them at suitable locations in the other Image. An important point here is to match the gradient of the spot weld mark image with the target image. A Poisson-based solution [6] for seamlessly merging the source image patch into the destination image has been used (Fig.2b).

Image Preprocessing and Segmentation of Individual Pin

The fuel bundle image used for the final visual inspection has 37 fuel pins welded with end plates. Hence, it is required to segment individual fuel pins for supervised training and classification with a neural network model. Following image preprocessing and segmentation algorithms are applied to produce boundary masks and isolated pin images for further processing (Fig.3):

- Image smoothing using the Gaussian Filter to remove noise.
- Edge detection with Laplace of Gaussian with Zero Crossing.
- Image Thresholding to get a binary image.
- Hough transforms with the tuned parameters to produce the Image's desired pins boundaries (mask).

The software developed uses the mask generated above and applies it to the input image for segmenting individual fuel pins. Thus, each fuel bundle image generates 37 fuel pin images for the training and classification of deep neural networks.

Deep Learning Architecture

Network-based on Inception and ResNet architecture (Fig.4) has achieved good performance for detecting spot weld marks as compared to typical deep learning architectures. The Inception ResNet block combines multiple filters of various sizes with residual connections. This feature not only helps in convergence but also reduces the training time of the network. This network has been pre-trained on a large dataset for object detection and segmentation. Our framework uses a transfer learning approach to classify three weld categories. Fig.5 shows isolated fuel pin images batch-processed by a deep learning network to produce superimposed classification results on fuel bundle images.

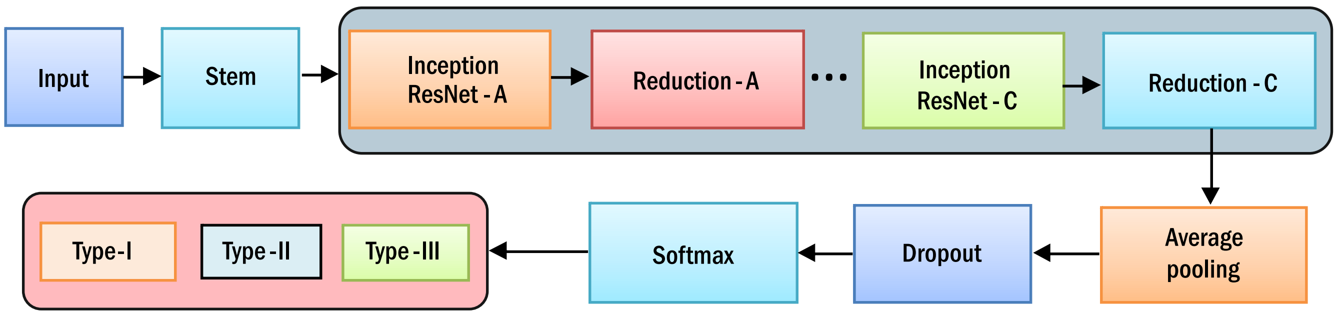


Fig.4: Deep learning architecture based on Inception ResNet-V2.

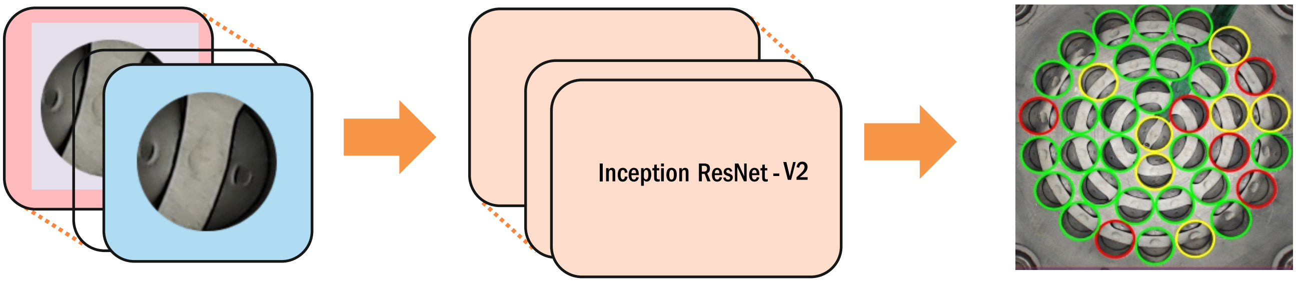


Fig.5:Inspection system based on deep learning system. Following convention is used for depiction of weld quality, Green: Type-I, Red: Type-II, Yellow: Type III.

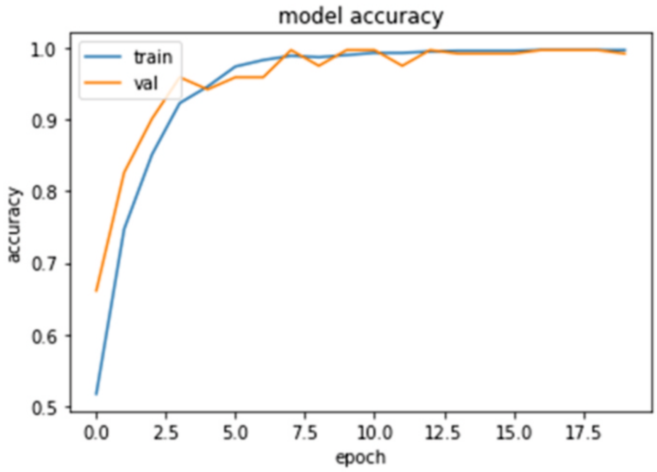


Fig.6: Training and validation accuracy of deep learning model.

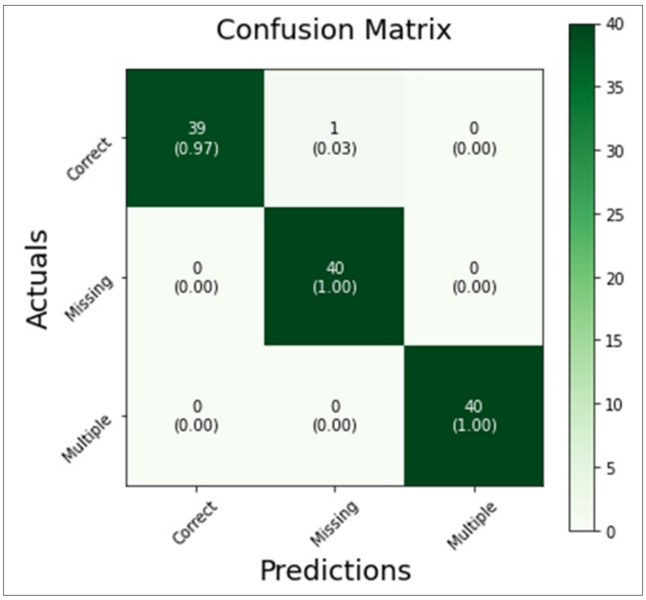


Fig.7: Evaluation of deep learning model with test data.

Results

We performed model training for 20 epochs on a total of 1200 images. The dataset used for training has uniform distribution across Type-I, Type-II, and Type-III instances (400 each). We also validated the model with 120 images (40 for each class). Fig.6 shows that both the training and the validation accuracy increased with the number of epochs, and there is no over fitting or under-fitting.

The training accuracy is 0.9928, and the validation accuracy is 0.9918. Fig.7 shows values of the confusion matrix over the predictions on the test data. There is only one misclassification, where Type I (Normal) classifies as Type II (Missing spot weld mark). Detail investigation revealed that the weld mark was barely visible due to the camera position. The mean precision and recall computed from the confusion matrix are 0.9918 and 0.9916, respectively.

Conclusions

We have developed a framework for automated inspection of end plate weld with nuclear fuel pins. The proposed method achieves mean precision of 0.9918 and a mean recall of 0.9916 with test images. Initial tests on the production floor show promising results. The system is undergoing rigorous performance testing by deliberately creating Type-II and Type-III spot welding marks.

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