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Evaluation of X-Ray Computed Tomography (CT) Images of Additively Manufactured Components using Deep Learning

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Abstract

Additive manufacturing (AM) enables building of lightweight components with very complex geometries. However, the presence of pores in these components is common due to process limitations. These internal defects affect the mechanical properties of the component leading to deficits in the performance and service life. Therefore, they must be reliably detected and accurately characterised.

Complex designs, commonly encountered in AM components, present insurmountable difficulties for traditional NDT approaches such as ultrasonic and eddy current methods.

In comparison, X-ray Computed Tomography (XCT) can scan complex internal components with relative ease. However, due to artefacts introduced by the scanning method and associated with the use of polychromatic X-ray beams, simple image processing methods do not work well in detecting micro defects such as pores or fine cracks.

Manual detection of pores in AM components with image processing tools requires a highly trained technician to scrutinise every slice in the scan, i.e. a manual procedure which is both unreliable and unproductive.

Machine learning has previously been shown to improve the quality of the pixel-wise classification of small pores close to a single voxel in size. In this study, we propose a deep learning method to train a mathematical model, based on millions of deep image features, for accurate defect detection and characterisation.

U-Net, an open-source deep-learning architecture was utilised to improve the classification accuracy of micro-porosity detection within an AM built component.

In this paper, an application of deep learning, using U-NET architecture, to accurately classify pores is presented.

The results show a significant improvement in the detectability of pixel-wise classification of pores compared to traditional machine learning models and image processing methods.

The data, taken from an XCT scanned images was used to train deep learning model to determine micro-porosity, and the result was compared to Archimedes density experimentation result performed on the same coupon.

Keywords: Artificial Intelligence, Deep Learning, U-Net, Fujitsu Engineering Cloud, XCT, X-ray, Computed Tomography, NDT, Additive Manufacturing

1   Introduction

Additive Manufacturing (AM) is a process of building a 3-dimensional object by creating a component layer by layer. The latest advancement in the technology allows industry and researchers to print a wider range of materials [1] including aerospace-grade metals such as Titanium and Inconel alloys.

This method has revolutionised the manufacturing industry and can be considered a disruptive innovation that opens a new frontier of discoveries.

Despite the promising future, the quality and material integrity of an AM component is highly dependent on the process parameters and build design. An unoptimized parameter may result in a porous component filled with unfused powder, which affects the material properties and the useful lifetime of the component.

XCT is one of the common methods of non-destructive evaluation during the development phase of an AM process. A micro-XCT scan typically captures pore information that is close to the voxel size. The result that is produced by XCT has been compared typically to Archimedes density, which is a standard method for porosity measurement for an additively manufactured component [2].

X-rays are created by colliding electrons, typically produced by a charged filament in a vacuum, into a metal target. Industrial X-rays can typically penetrate through a dense metal component.

An industrial XCT scan of a dense metal object is usually dominated with artefacts such as beam hardening and incoherent scattering [3]. This means that the scanning result gets blurry and it is difficult for traditional image processing techniques to segment the images accurately.

The solution presented in this paper looks to improve the detectability of pores in an additively manufactured component using deep learning.

2   Reference Component

The design of the reference component was catered for Archimedes density measurement; a method of pore quantification based on relative density measurement [4]. A cylindrical component with a diameter of 13 mm was designed, printed and post-processed to remove surface roughness dependencies in the Archimedes density measurement.

Versions of the component were produced in three aerospace-grade materials; Ti-64, MS1, and AlSi10Mg. Samples were printed with different settings using an EOS M290 3D-printer to vary the print quality in the component. The diagram in Figure 1 illustrates the improvement of surface condition of the sample component. On the left is the condition as printed and on the right is the condition after turning and grinding prior to Archimedes density measurement.

Figure 1. Specimen for X-ray and Archimedes density measurement

3   Deep Learning based Model

Deep learning is a type of machine learning in which the algorithm learns to look for deep features in data. It was inspired by how the human brain works to process input signals [5]. It consists of the basic features of a neural network such as neurons or nodes, which multiplies a set of input data with trainable weights, sums it up followed by an activation function. These sets of nodes are connected to form a simple artificial neural network.

U-NET [6] is an artificial neural network that works by such a principle. It multiplies a set of data input, linearizing the sum, and lowering down the dimensions by the max-pooling method, while concatenating the information of the layer to the corresponding up-sampling layer. (illustrated in Figure 2)
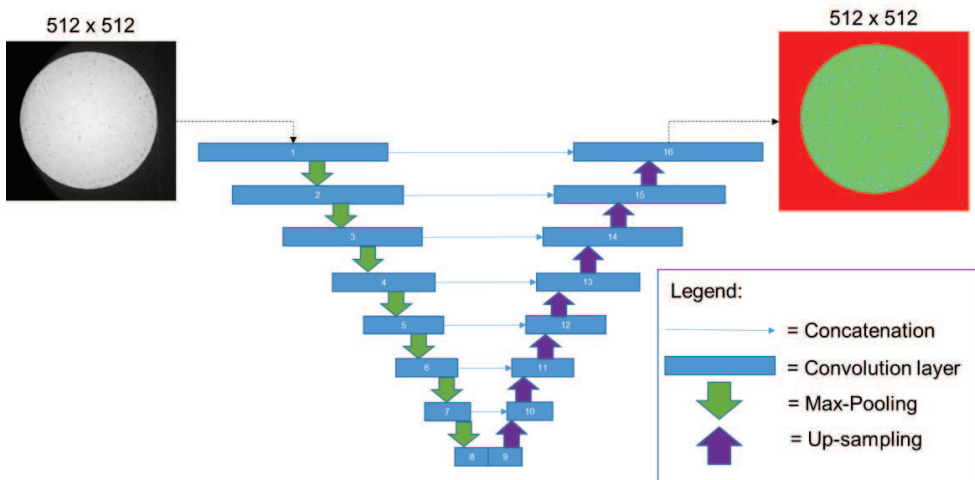

Figure 2.U-Net layer

U-net was originally developed for biological microscopy images, where the concatenation layer within the network maintains the shallow information within the image at the output so that the intrinsic information that is carried by the small features is not lost due to down-sampling. This makes this network ideal to classify micro-pores which are usually only a few pixels in size.

4   Image Labelling

The model aims to accurately classify the pores as close as possible to a human operator. Hence the training set has to be verified and developed by a human operator.

In the previous study [7], it has been shown that random forest; a common machine learning algorithm, can be utilised to reduce false detection compared to that of a traditional method. However, as it still has erroneous output, a human operator needs to verify and, if needed, alter the machine learning segmentation to give a more accurate result according to the trained inspector's judgement.

Fiji [8] an open-source software was used to do pre-segmentation classification with the help of random forest algorithm. The segmented image was then checked, and corrected manually by an operator. The result is illustrated in Figure 3.
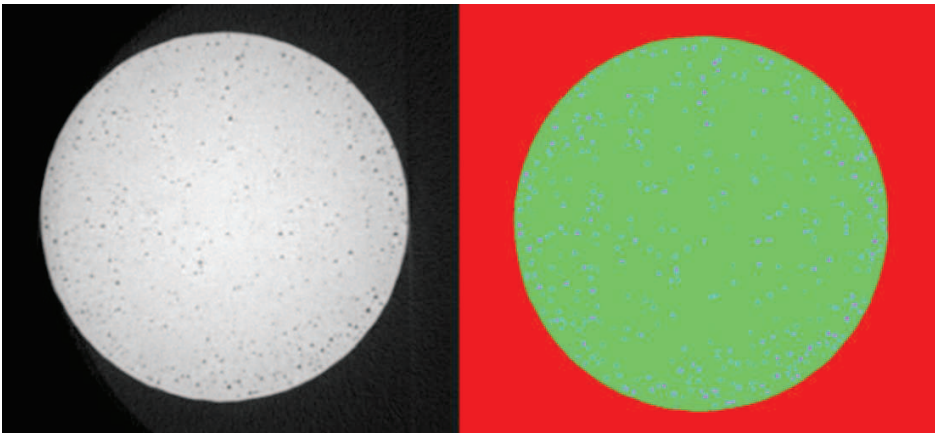

Figure 3. Machine-learning assisted training image

5   Model Training

The training of U-net was conducted with different hyperparameter settings. Essentially, these training variables will affect the overall accuracy. Batch size is the number of images that are trained per step, and the steps are the number of batches of images that are taken per epoch. Ideally, larger the batch size, the model will "experience" more images and hence will be generally able to classify defect in a more varying dataset. However, larger batch size will require more GPU processing, and hence there is a hardware limitation on what hyperparameter can be set.
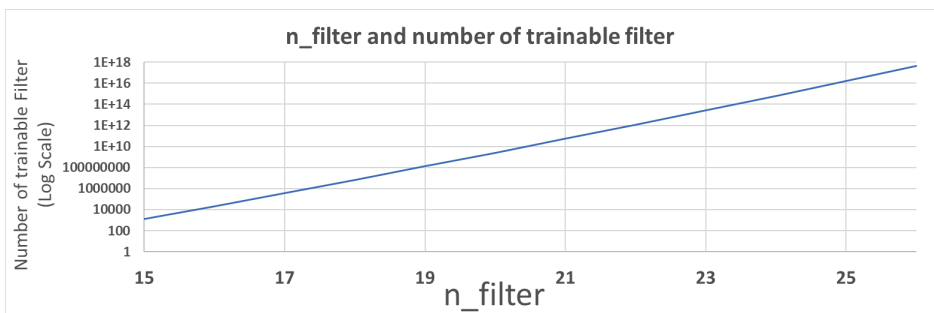

Figure 4. The number of filter variables increments against trainable filter

n_filter variable denotes the number of convolutional filters in U-net architecture. The number of trainable filters increases exponentially as the n_filter parameter is increased (shown in Figure 4). Hence each incremental step of this variable requires a significantly larger processing demand.

To train this model, Fujitsu's Engineering Cloud [9] Server was used with the following hardware specification;

Hardware	System Specification
Operating System	Windows Server 2012 R2
CPU	Intel® XEON® E5-1650 v4 @3.60 GHz (6 Core)
RAM	128 GB
Graphics Card	NVIDIA Quadro P5000

Table 1. Hardware Specification for model training

In many instances, a particular set of parameters saturates the memory, due to the number of calculations needed, and hence crashes the system. To automate the training, it is recommended to design a closed-loop system (illustrated in Figure 5), with the output accuracy value to be written in a CSV document. This way, an automatic hyperparameter optimisation can be achieved with little interference from the user.
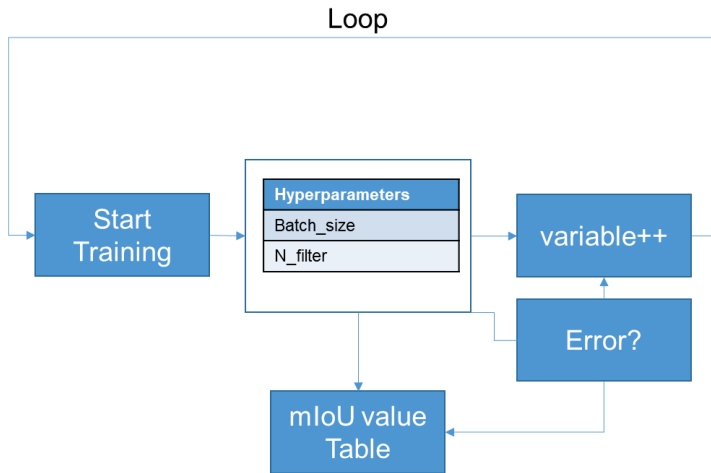

Figure 5. Training loop

To quantify accuracy, a mean intersection over union (mIoU) value is used to represent the performance of the model. To calculate mIoU, the area of overlap between the ground truth and predicted image is divided by the total area of union for both ground truth and predicted output as illustrated in Figure 6.
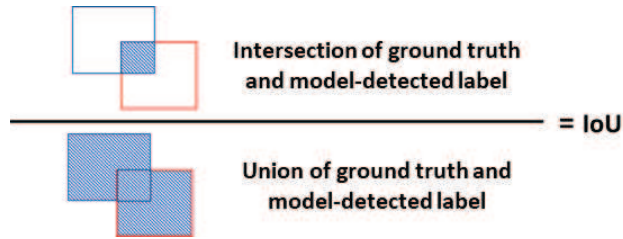
Figure 6. Intersection over Union (IoU) calculation

mIoU represents the percentage overlap of the ground truth image to the predicted pixels. The closer the value is to 1, the better the model is in predicting the defects.

6   Results & Discussion

The result shows that hyperparameter optimisation has a significant effect on the overall performance of the model. A non-optimised U-net model yields less than 65% mIoU while optimised hyperparameters yield above 80% mIoU.

This result suggests that the model parameter values affect the overall accuracy of the model. A larger value of the n_filter variable tends to improve the model performance. However, to keep increasing it may require much higher computing and hence there is a hardware limitation stop to the number of filters that can be set for training.

Settings no.	mIoU	Batch Size	n_filter	Epoch	Steps
1	0.631	5	16	150	10
2	0.748	5	16	150	10
3	0.851	5	18	150	10
4	0.655	5	18	150	11
5	0.742	1	20	150	11
6	0.819	1	20	500	11
7	0.833	1	20	500	10

Table 2. Hyperparameter optimisation

Apart from the number of filters, ideally, it is recommended to keep the batch size as high as possible. However, the increase of the batch size will also be limited by the hardware's ability to perform the calculation and hence has to be balanced with the other variables.

In this case, the model was trained on 378 training images, and the best result was obtained with the batch size of 5 and steps of 10. It requires a large number of epochs for the model to be trained on all the images. Hence training epoch above 500 is recommended.

To improve the detection further, image augmentation can be done to alter the images and to increase the training set. The Keras [10] library has direct functions to augment the images without manual tweaking. Three functions (random zooming, rotation of the image, and applying random brightness to the object) were explored and the results are plotted in Table 3..

This function essentially alters the training and ground truth images to make the model more robust to feature changes from one image to another.

Settings no.	Val_mIoU	Augmentation
1	0.927	Zoom
2	0.894	Rotate
3	0.902	Random Brightness

Table 3. mIoU improvement after Image Augmentation

Image augmentation can be used to further train the model if there is insufficient training data. If the component is non-symmetrical the rotation function is useful to generate more randomness in the image for the model to understand.

Zooming function is essentially useful in improving the detectability of small features as it enlarges the size of the pores and allows the model to train the image on deeper filters. This allows the model to understand the hierarchy of the features and improves the differentiation factors between the defects and noise.

Using random augmentation function, the overall pore detectability increases significantly to 92.7% under random zooming with default range. This shows that the image augmentation is a necessary step to improve the model to the maximum possible accuracy.

To compare the accuracy of the model against Archimedes density measurement, the data was post-processed, and the pixels that belong to class pore are calculated.

The result shows a significant correlation between AI and Archimedes values. The distribution diagram shown in Figure 7 shows the deviation spread of 20 cylindrical samples that were CT-scanned and measured by Archimedes density measurement.
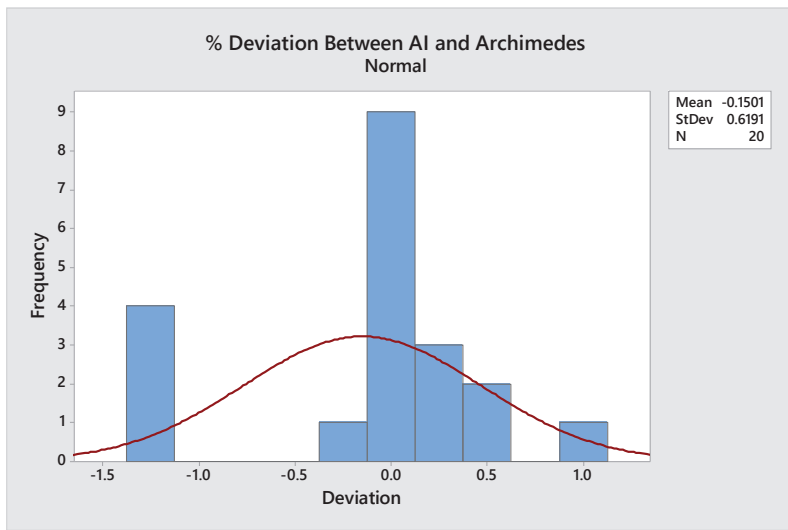

Figure 7. Distribution of Deviation against Archimedes Density

For most of the data, the deviation value is less than 0.62%, here represented by the standard deviation value in Figure 7. The average deviation is 0.15% which represents the accuracy of the measurement, using Archimedes density measurement value as the reference point.

The difference in the measurement could be attributed to the uncertainty in the Archimedes density measurement that can be contributed by the purity of the acetone, or the instrument's accuracy.

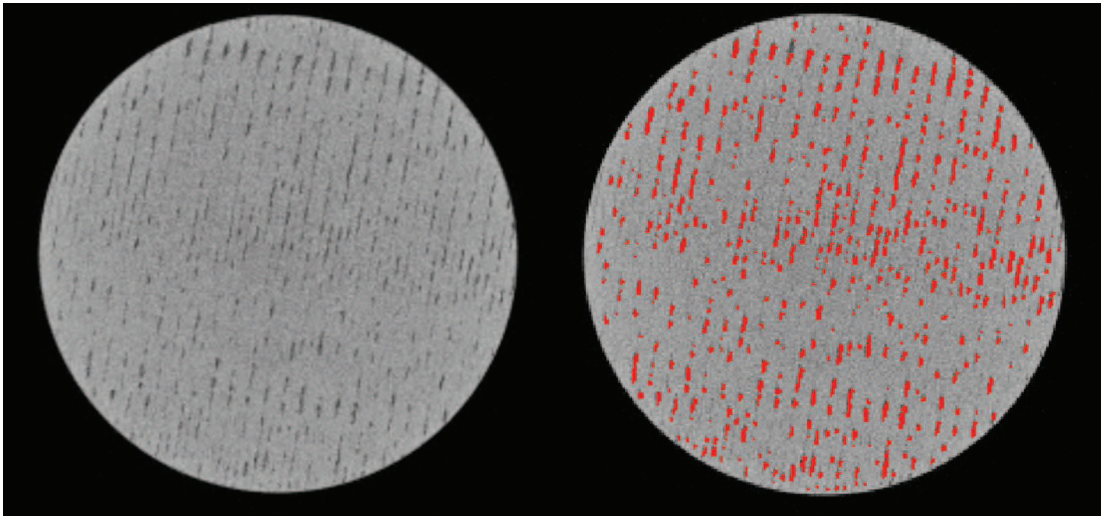When plotted visually, the data shows a good segmentation result as shown in Figure 8.

Figure 8. [Left] Raw reconstructed data [Right] pore segmentation using U-net

The result shows that the detection accuracy closely matches the actual defect presented. This means that U-net can be used to significantly cut down post-processing time and to improve accuracy compared to that of a traditional image processing approach.

7   Summary and Further Research

In conclusion, the capability of deep learning to accurately segment slices of XCT reconstructed data with the presence of X-ray artefacts was demonstrated. This suggests that deep learning has a strong application within the Industrial X-ray CT domain to improve the process quality and productivity. U-net with image augmentation result yields above 92% detection accuracy, significantly improving the quality.

Further research is required to improve the detectability and the speed of detection. Redesigning the neural network architecture may be required to reduce redundant layers and to extract useful image features more effectively.

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