euspen's 24th International Conference & Exhibition, Dublin, IE, June 2024
www.euspen.eu

An adaptive deep learning based approach to classification and labelling of image data from Additive Manufacturing

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Abstract

Advances in computer vision and in-situ monitoring, facilitated by visual sensors, enable the acquisition of extensive image datasets from the additive manufacturing (AM) process. These datasets hold significant potential for improving the quality of AM through the application of machine learning techniques. Despite the increased availability of such data, subsequent data analytics such as classification and labelling, are typically manual which does not scale and allows errors as a result of the manual process.
This paper provides a deep learning model developed for classification of image data from the AM process, along with the relevant methodology for training, labelling and associated experiments. We present an approach that employs a convolutional neural network (CNN) based classifier in combination with transfer learning and active learning strategies and we explore the minimum number of labelled images required to achieve convergence during the training process, with a focus on optimising data efficiency. Our classifier serves as a robust foundation, allowing further advances in the labelling mechanism which involves leveraging semi-supervised learning techniques with the integration of human-in-the-loop. This approach augments and refines the labelling process, capitalising on the strengths of both automated learning and human supervision to further enhance the accuracy of the labelling, the performance of the model and the applicability of our approach in the domain of additive manufacturing.

Keywords: 3D printing, artificial intelligence, classification, neural network

1. Introduction

Given rapid developments in data collocation in the domain of Additive Manufacturing (AM), the datasets developed from such collected data have potential for determining the quality of the manufactured output and the detection of defects through the use of Machine Learning (ML) during the manufacturing process. However, rather than concentrating on the method for data collection, this paper focuses on the processing and utilization of image data in ML applications which support AM.

Large and open-source datasets of annotated images containing up to millions of training examples such as ImageNet [1] which contains more than 14 million annotated images and COCO (Common Objects in Context) [2] which contains more than 200 000 labelled images, have allowed machine learning to develop hugely in recent years. This is partly due to the fact that the datasets are open, easily available and re-used by many researchers. However, to create such datasets specific to the domain of AM is still difficult because acquiring process monitoring data with annotations is cost-prohibitive in AM as shown by Manan and Shao [3]. A recent survey on the topic of image datasets [4] clearly states that sample images from the AM process, labelled with annotations of microstructure defects in the manufacture, are often difficult, expensive, and time-consuming to obtain, which creates challenges in the application of vision-related machine learning in AM.

In many practical situations, collocated image data from AM processes have a limited number of properly labelled samples and a large volume of unlabelled samples. Some researchers have named this situation the ``Small Data Challenge in Big Data Era" [5]. Consequently, it is desirable to have a machine learning methodology that can begin with the utilisation of the small number of labelled samples then further leverage the large number of unlabelled data to develop more labelled samples from unlabelled images. This helps to improve the performance of the ML model to achieve higher accuracy.

To overcome the challenge of providing a neural network model with limited labelled data samples, we present a method that applies transfer learning and fine-tuning on a convolutional neural network (CNN)-based neural network model to achieve improved classification on the image samples. Then, based on the outcome of the initial classification model, our methodology then involves active learning algorithms, which identifies the most informative data samples for the model to learn from as a higher priority. This reduces the number of labelled samples required in the training process. Finally, by utilising the combination of an active query strategy and a semi-supervised learning technique with Human-In-The-Loop (HITL) features, we perform automatic labelling using the model to generate larger datasets of labelled images from unlabelled samples.

2. Background knowledge

Transfer learning is a method that performs training a neural network model using data from a source domain then later applying the trained model to a target domain, different from the source. This allows rapid progress in re-training and significantly reduces the required number of training samples in the target domain. This is commonly used in computer vision tasks such as classification to support improved performance in domains which are data-poor. In recent years, transfer learning has proved to be effective in the task of defect classification in AM, such as the work presented in [6] and [7] where transfer learning and fine-tuning were applied to training a CNN based neural network architecture.

Active learning [8] is a technique for labelling data that selects and prioritises the most informative data points for an annotator to label. Such prioritised data points have the highest potential impact on the supervised training of a machine learning model, thus improving the overall training process. The combination of transfer learning and active learning allows leveraging small amounts of labelled data to improve the performance of the training process.

Semi-Supervised Learning [9] leverages both labelled and unlabelled data to improve model performance. Among Semi-Supervised Learning techniques, Pseudo-Labelling [10], stands out as a simple but highly efficient method, which can be summarised in 3 distinct stages:

1. Using available labelled data, build an initial model.
2. Generate pseudo labels for the unlabelled data using the model.
3. Further train the model using both the original labels and pseudo labels. This additional training phase fine-tunes the model based on the augmented dataset.

However, it has 3 major drawbacks and limitations as follows:

1. If the initial model is poor or biased, pseudo-labels may also be inaccurate, leading to a propagation of errors.
2. Significant distribution mismatches between classes in the training may lead to the class imbalance issue.
3. The lack of feedback or correction mechanisms for mistakes on labels brings a risk of noise amplification.

Methods to apply these techniques in our approach and approaches to address related problems are illustrated in the next section.

3. Method

Our methodology involved the creation of a CNN-based initial model for classification followed by active learning-assisted training and semi-supervised labelling, with human supervision.

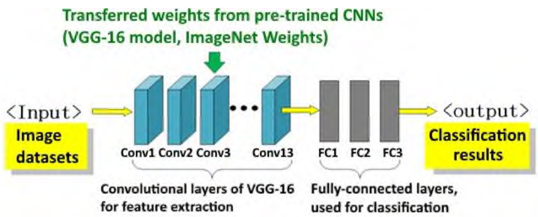

Figure 1. Architecture of our model based on VGG 16 and fully connected layers.

3.1. CNN based initial model

Our CNN based initial model relies on transfer learning in which 13 convolutional layers from a pre-trained VGG16 model [11] are used for feature extraction, the weights having been trained using ImageNet data. After the convolutional layers, 2 fully-connected layers with a ReLU activation function are added followed by 1 fully-connected layer as the output layer using Sigmoid as the activation function, since the targeted dataset is divided into 2 classes for binary classification. The architecture of this CNN based initial model is shown in Figure 1. The implementation was conducted using Python 3, Keras and scikit-learn machine learning packages within the Google Colab environment.

3.2. Fine-tuning with image datasets

To investigate the adaptability of the CNN-based model, 3 datasets with 8 different types of patterns have been tested individually by applying fine-tuning on the model. The 3 image datasets are emission images [12], DAGM patterns [13] and images from Selective Laser Sintering (SLS) [8]. Figure 2 shows examples of patterns from each dataset.

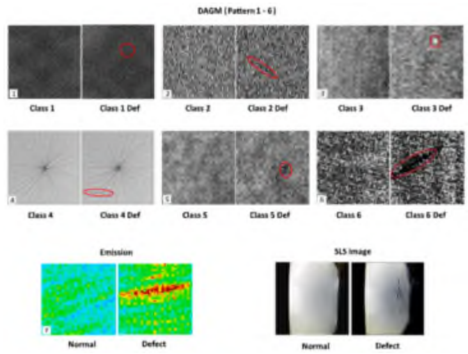

Figure 2. Examples of patterns from emission, DAGM and SLS

The emission image dataset is developed from the emission data collected by the InfiniAM monitoring suite from a Renishaw 3D printer during printing of Ti6Al4V parts. After post-processing, the dataset consists of 150 negative and 150 positive samples.

The DAGM dataset is inspired by problems from industrial image processing, where automatic visual defect detection has the potential to reduce the cost of quality assurance significantly. The DAGM datasets involves 6 different patterns while each pattern is divided into 2 classes: defect (150 samples) and normal (1000 samples). This dataset offers support to test the adaptability of our deep learning approach in the early stages when large-scale annotated image datasets are not available in the AM domain [14].

The SLS dataset contains 4,000 images, manually divided into 2 defect detection classes. The images in this dataset are separated into 3 subsets for training (2,000), testing (1,000) and validation (1,000). The dataset is used in later stages of our research on active learning assisted training and semi-supervised learning labelling.

Table 1. hyperparameters used for the training/tuning of the deep learning model

Name	Type/Value	Description
Optimizer	Adam, SGD, RMSprop	Optimizers are used to change the attributes of the neural network to reduce the losses
Loss function	binary cross entropy	Loss function computes the quantity that a model should seek to minimize during training
Learning rate	10^{-2} to 10^{-5}	The step size at each iteration while moving toward a minimum of a loss function during the training process
Batch size	4, 32, 64	The number of training samples utilized in one update of the model's parameters.
Evaluation metric	Accuracy, Loss	Function to judge the performance of the model

During the fine-tuning process of the model, combinations of hyperparameters are investigated through multiple tests using different settings. Tuning hyperparameters involves adjusting the optimiser, learning rate, batch size and training epochs. We use 3 optimisers namely Adaptive Moment Estimation (Adam), Stochastic Gradient Descent (SGD) and Root Mean Square Propagation (RMSprop) in combination with different ranges of learning rate, batch sizes and training epochs. The cost function used in all tests is binary cross entropy. The tested values for the hyperparameters during the tuning process with relevant descriptions for each are shown in Table 1. Moreover, to combat overfitting, we introduced weight regularisers to the two dense layers employing the ReLU activation function, as previously mentioned. We applied weight decay regularisation, also referred to as L2 regularisation, which calculates the sum of squared weights. The hyperparameter tuning for weight decay regularisation spanned a range from 10^{-1} to 10^{-4} and was tested multiple times until overfitting issues no longer surfaced during training and validation. This tuning process aimed to keep a balance between model complexity and generalisation ability, ensuring the model's robustness.

Classification results on different image patterns are presented in Table 2. It is worth noting that the relationship between hyperparameters and performance is problem-dependent, and the effectiveness of a specific hyperparameter, such as batch size, can vary for different datasets and models.

Table 2. Classification results from the CNN based model with transfer learning and fine-tuning

Patterns	Avg. Val Accuracy	Avg. Val Loss	Training (epochs)
Emission	0.981	0.03	200
DAGM1	0.964	0.09	200
DAGM2	0.983	0.03	200
DAGM3	0.962	0.10	200
DAGM4	0.965	0.09	200
DAGM5	0.982	0.04	200
DAGM6	0.959	0.09	200
SLS	0.979	0.05	200

3.3. Active learning to further optimise training

With the setting up of the CNN based classifier model that effectively uses domain transfer principles across the additive manufacturing image datasets, our research makes progress to extend beyond conventional training methodologies. The active learning approach introduced a query strategy to the training of the classification model, enabling it to iteratively improve its performance by strategically selecting and labelling the most informative data samples to be used. This iterative approach allowed us to make efficient use of the labelled data and to optimise the performance of the model through active data selection. This approach was conducted through a series of steps, performing a structured and iterative approach with the following key stages: (1) active sample section, (2) query for label, (3) train with queried sample, and (4) validate for current query iteration. The cycle iterates until a human supervisor decides to complete the training phase when validation accuracy achieves a target level. Here we apply a pool-based sampling scenario and an uncertainty sampling query strategy [8]. This is the most commonly used query strategy to start generalised sampling on AM image datasets. In our previous work [15], this approach has been proven as highly sample-efficient on the SLS image dataset by Westphal *et al*. [7] during training of the model and achieves an accuracy level of over 98% in validation. This query strategy is also utilised in the development of our semi-supervised labelling method to address class imbalance and assist on the feedback mechanism with HITL.

3.4. Labelling using semi-supervised learning with HITL

The labelling mechanism involves leveraging semi-supervised learning techniques with the integration of HITL features, aims to augment and refine the labelling process by capitalising on the strengths of both automated learning and human supervision. This further enhances the accuracy of labelling, the performance of the model and the applicability of the approach in the domain of additive manufacturing defect detection. Our proposed labelling approach can be summarised into the following 4 steps: (1) Generate pseudo-label using the trained classifier. (2) Active selection according to uncertainty and human correction on the incorrect labelled samples in the selected pseudo-labels. (3) Create a new training batch by re-sampling to address the class imbalance issues then update the classifier using the training batch. (4) Evaluate the performance of the updated classifier on the rest of the pseudo-labelled data and the original validation dataset.

3.5. Class imbalance issue

When the labels obtained for model training are a significant distribution mismatch between classes, the trained models show a bias towards the majority class. Consequently, instances belonging to the minority class tend to misclassify at a greater rate. This is particularly problematic when the class of interest corresponds to the minority class. In AM datasets, defects mostly show within the minority subset of the total data population. For this reason, when forming a new set of training data from the results of pseudo-labelling, the class imbalance problem should be considered in order to avoid over emphasis on the major class.

To address this issue, we present an approach that combines uncertainty sampling with image data augmentation. This method places a strong emphasis on selecting the most informative samples, by identifying instances where the model exhibits uncertainty in its predictions. These informative samples are then systematically re-sampled using image data augmentation techniques, including transformations such as rotation, scaling, flipping, and cropping according to the relevant data structures. The objective is to generate a diverse set of new samples while preserving spatial correlations and image quality. This approach stands out as more preferable compared to synthetic image data generation, especially in the context of additive manufacturing, where data reliability and fidelity are extremely important.

4. Experimental results

In this section, we introduce our experimental process encompassing the labelling mechanism specifically focusing on an imbalanced dataset that developed from the SLS dataset. The sequence commences with the generation of pseudo labels utilising the initial classifier. Subsequently, active sample selection and human correction steps are employed to curtail the count of incorrectly assigned pseudo labels. Following this correction phase, the rectified samples are re-sampled to create a balanced batch, which is then used to further fine-tune the classifier.

4.1. Experiments on the imbalanced dataset

Experiments are conducted to evaluate the performance of our approach on an imbalanced dataset. The imbalanced dataset is derived from the testing dataset, which initially consisted of a balanced set of 500 defect samples and 499 normal samples (out of the 500 normal samples, one image was corrupted). For the imbalanced dataset, we randomly selected 101 defect samples from the original dataset and combined them with the 499 normal samples, resulting in a new dataset with an imbalanced distribution totalling 600 samples. After initial classification on all the testing data to obtain pseudo-labels, the relevant classification results are shown in Table 3 and the ROC curve is shown in Figure 3.

Table 3. Results of pseudo labelling on the imbalanced dataset

Accuracy	Precision	Recall	F1	ROC-AUC
0.982	0.917	0.980	0.947	0.997

In the initial classification task to obtain pseudo-labels, from the confusion matrix, there are only 2 samples from the minority class and 9 samples from the majority class, which are the defect and normal class respectively, that are incorrectly labelled yielding 11 mistakes out of the total of 600

4.2. human correction and re-sampling

As further investigation, we conducted active sample selection based on the uncertainty sampling method and queried for 50 samples that are calculated as the most informative for human correction. The uncertainty sampling and human supervision results in 2 samples from the true defect class and 2 from the true normal class to be corrected. Thus, after human correction, all the defect samples are correctly labelled in this particular labelling process.

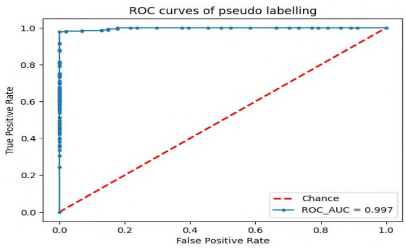

Figure 3. The ROC curves of the pseudo labelling using initial model

To address the class imbalance issue within the selected 50 samples, we conducted an examination of the class distribution of the samples which revealed that 10 samples belong to the minority class (defect), while the remaining 40 samples were from the majority class (normal). To achieve a balance between the two classes, we applied oversampling by augmenting the 10 minority class samples while retaining only the first 20 most informative samples from the majority class using an uncertainty sampling strategy. The 40 balanced samples were then added to the training data for further updating the model. To check the change in performance, the classification results on the validation dataset using the updated model are shown in Table 4.

Table 4. Results of the updated model on the validation dataset compared to the initial model

Classifier	Accuracy	Precision	Recall	F1	ROC-AUC
Initial	0.978	0.984	0.972	0.978	0.993
Updated	0.989	0.992	0.986	0.989	0.995

While our model enhances classification accuracy, it is worth noting that the absolute improvements obtained may appear relatively small due to the fact that the initial accuracies of the baseline are already quite high. Nevertheless, our primary objective was to demonstrate how HITL features can further enhance the performance of the classification model, even when starting from a high baseline level.

Using this updated classification model, we performed auto labelling again on the remaining imbalanced testing dataset, the labelling performance is shown in Table 5. Since there is no mislabelling in the minority class, the value of recall is 1 which means for this particular dataset, all the defect samples have been correctly classified. As this is a computer vision-based ML application for classification on images datasets, the results are based on ML models for classification using features extracted from the AM process, such as power bed defects in SLS. The condition of the powder significantly influences the performance of SLS sintered parts, making machine learning applications for monitoring powder bed conditions highly promising for defect detection, manufacturing efficiency, and non-destructive quality assurance.

Table 5. Evaluation of pseudo labelling on the imbalanced dataset using updated model

Accuracy	Precision	Recall	F1	ROC-AUC
0.989	0.929	1.00	0.963	0.999

5. Conclusion

This paper presents an approach that performs computer vision-based classification and labelling on image data from the additive manufacturing process. We use a CNN-based classifier in combination with transfer learning, active learning strategies and semi-supervised learning to overcome the small data challenge. We achieved accurate classification in different pattens and labelling work on an SLS image dataset. In future work we plan to further investigate the sampling strategies for active learning and to refine the labelling method.

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