Deep transfer learning of additive manufacturing mechanisms across materials in metal-based laser powder bed fusion process

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ARTICLE INFO

Associate Editor: Dr. Jian Cao

Keywords:
Powder bed fusion
In-situ monitoring
Wavelet Transform
Convolutional neural network
Transfer learning

ABSTRACT

The defective regimes in metal-based Laser Powder Bed Fusion (LPBF) processes can be minimized by deploying in-situ monitoring strategies comprising Machine learning (ML) algorithms and sensing techniques. So far, algorithms trained for monitoring a particular material type cannot be re-used to monitor another material in Additive Manufacturing (AM). This is a topic rarely researched in AM. Inspired by the idea of transfer learning in ML, we demonstrate the knowledge learned by the two native Deep Learning (DL) networks, namely VGG and ResNets, on four LPBF process mechanisms such as balling, Lack of Fusion (LoF) pores, conduction mode, and keyhole pores in stainless steel (316L) can be transferred to bronze (CuSn8). In this work, the spectrograms computed using Wavelet Transforms (WT) on Acoustic Emissions (AE) during the LPBF process of stainless steel and bronze are used for training the two DL networks. Either network is first trained for classification by spectrograms representing four mechanisms during the processing of stainless steel. The trained model is then re-trained using transfer learning with spectrograms from bronze data for a similar classification task. The accuracy of the two networks during transfer learning shows that it is effectively possible to learn transferable features from one material to another with minimum network training time and dataset collection.

1. Introduction

Additive manufacturing (AM) has become a prominent method in fabricating complicated and intricate shapes in leading industrial sectors compared to the traditional manufacturing techniques (Tapia and Elwany, 2014). AM offers advantages such as minimum wastage of material and a cleaner production environment compared to subtractive machining techniques that were traditionally practiced. Laser Powder Bed Fusion (LPBF) is a variant among metal additive manufacturing techniques that have been quite well known for a while and are the most investigated. In LPBF, the parts are built in sequential layers. A laser beam moves around a powder bed of thickness ranging from 20 to 60 µm prepared by a re-coater mechanism. The laser irradiation melts and fuses the particles in a powder bed with their neighboring layers as well as with adjacent particles in the same layer. The laser irradiation scans are performed selectively by moving optical elements in the laser head based on the original 3D computer-aided design (CAD). The process of irradiating and refilling the powder bed continues until the whole part is built, typically going up to thousands of layers.

Building parts without defects in processing a specific material involves choosing optimum parameter levels to achieve desired properties. Numerous parameters such as laser power (Spears and Gold, 2016), scanning speed (EsmaeiliZadeh et al., 2020), scanning pattern (Liu et al., 2021), the material composition of the powder (Knieps et al., 2021), surrounding environment (Ch et al., 2019), laser beam size (Gerstgrasser et al., 2021), etc., affect the LPBF process quality. During the process, any deviation from the optimum window parameters for any material causes significant changes in the laser-material interaction affecting the melt pool’s depth, width, and length. The resulting melt pool geometry influences the quality of the built part. Conversely, unfavourable melt pool geometries lead to the formation of defect mechanisms such as balling, porosity, LoF pores, delamination, cracks and deviation from the desired microstructure. Some effects of the parameters on laser-material interaction and the corresponding defect mechanism are listed in Table 1.

At present, the industrial standard for non-destructive examination
of the build quality regarding the defect mechanisms listed in Table 1 is carried out via off-line quality control methods such as X-ray tomography (Maskery et al., 2016), ultrasonic inspection (Rieder et al., 2016), etc. The major disadvantage of off-line methods is that it does not allow taking corrective actions on the occurrence of the defect, resulting in wastage of the material and valuable manpower and machine time. Though LPBF techniques have made some progress concerning building parts out of different materials, production speed, machine construction, etc., the technology still lacks repeatability. Hence, there is a need for robust and cost-effective in-situ quality monitoring systems, but their development is in the early stages. Understanding the defect mechanism formation is crucial for such development, followed by strategies to suppress these defect formations. The defect mechanisms can be understood with the help of suitable sensing (Everton et al., 2016) and signal processing techniques (Pandiyan et al., 2020). With mechanisms happening in the order of microseconds, sensors should have good sensitivity along with high spatial and temporal resolution. Sensors such as pyrometer (Artiz et al., 2020), infrared imaging (Grasso et al., 2019), cameras (Scime et al., 2020), optoacoustic (Gutknecht et al., 2021), acoustics (Shevchik et al., 2019), etc., have been reported in the literature for monitoring the melt pool dynamics and the defect mechanisms. One promising approach for automatic detection of defects is using a Machine Learning (ML) algorithm capable enough to recognize patterns from the sensor signature.

Craeghs et al. (2010) demonstrated that based on the response of the photodiode sensor, the laser power can be altered by a feedback control loop in real-time. Craeghs et al. (2012) have also mapped the melt pool and thermal behaviour with a high-speed camera and a photodiode for monitoring the build. Photodiodes and semiconductor (CMOS) cameras have also been used to detect process failures based on the interpretation of the melt pool dynamics (Clijsters et al., 2014). Berumen et al. (2010) showed that coaxially mounted cameras can be used to monitor the shape and size of the melt pool. Solidification mechanisms of the melt pool have been studied by correlating the surface temperature with the pyrometer (Furumoto et al., 2013). Detection of unstable behaviors in the process has been demonstrated by infrared imaging of the melt pool (Grasso et al., 2018). The plume properties for challenging materials like zinc and its alloys have been imaged using infra-red sensors for in-process sensing (Grasso et al., 2018).

The dimensions of the melt pools in the LPBF process range between 50 and 250 µm and appear for a few microseconds. Monitoring systems based on visual and optical sensors require high spatial and temporal resolution to capture these phenomena, making them very expensive. Additionally, the cost for processing the data from these sensors are also high as they require heavy computational resource. Alternatively, AE air-borne and structure-borne sensors with the reliable temporal resolution are proposed as an economical solution for monitoring the additive manufacturing process (Shevchik et al., 2019). Pandiyan et al. (2020) have demonstrated that air-borne acoustics captured across four different LPBF regimes exhibited different characteristics in time, frequency and time-frequency domains. Gutknecht et al. (2021) presented that AE has 40 times higher sensitivity than the camera and 15 times more sensitive than the pyrometer in detecting flaws. Furthermore, AE events have been correlated with the location of the micro defects that occur in the LPBF process (Ito et al., 2021). A defect detection system based on a deep belief network (DBN) and microphone data have been successfully developed to classify balling and other mechanisms (Ye et al., 2018). Shevchik et al. (2019) developed a spectral convolutional neural network classifier to distinguish the acoustic features for different mechanisms occurring in the LPBF process. Generative models such as Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs) has been applied on acoustic signatures corresponding to different laser regime in LPBF to distinguish defect-free regimes from anomalies (Pandiyan et al., 2021). A bi-stream Deep Convolutional Neural Network (DCNN) trained with images acquired during the LPBF layering process was able to identify defective conditions (Caggiano et al., 2019). Unsupervised machine learning algorithms have also been implemented to detect and classify anomalies in the LPBF process (Scime and Beuth, 2018). A few review works have extensively reported the application of ML techniques for monitoring 3D printing. Yu and Jiang (2020) focused their review on 3D bioprinting; Meng et al. (2020) wrote their review from the perspective of the ML algorithms; whereas Goh et al. (2021) concentrated not only on the application but also challenges and potential of ML in AM processes.

The in-situ monitoring techniques based on ML have been successfully demonstrated for various base materials such as Stainless-steel (Eschner et al., 2018), Bronze (Scime et al., 2020), Inconel (Pandiyan et al., 2021) and Titanium (Kouprianoff et al., 2021). Owing to the significant differences in optical and thermal physical properties of the base powder particles, the experimental parameters listed in Table 1 vary considerably for the occurrence of defect mechanisms among the different materials. It is well-known that the melt pools formed are mainly a function of the powder material and thermodynamic properties. As a result, there would be a change in the distribution of process

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Parameter level</th>
<th>Mechanism evolved</th>
<th>Remarks on laser-material interaction</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Laser power</td>
<td>High</td>
<td>Cracks, Distortion and keyhole pore formation</td>
<td>• Evaporation of material, the occurrence of residual stresses</td>
<td>(Simon et al., 2017)</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>Balling</td>
<td>• Weak flowability of the melt pool resulting in a small contact area to the substrate</td>
<td>(Li et al., 2012)</td>
</tr>
<tr>
<td>Beam quality, intensity profile, spot size</td>
<td>–</td>
<td>Microstructure</td>
<td>• Less likelihood of powder ablation and plasma formation resulting in low absorptivity</td>
<td>(Li et al., 2012)</td>
</tr>
<tr>
<td>Scanning speed</td>
<td>High</td>
<td>Balling</td>
<td>• Neighbouring scan tracks are not connected sufficiently</td>
<td>(McLouth et al., 2018)</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>Thermal-induced cracks</td>
<td>• Affects the spatial distribution of energy delivered and the cooling rate</td>
<td></td>
</tr>
<tr>
<td>Scan pattern/ strategy</td>
<td>–</td>
<td>Delamination, Microstructure, Thermal induced cracks</td>
<td>• Influences the heat transfer with the environment in the vicinity of the melt pool and also energy absorption due to modified surface morphology from previous scans</td>
<td>(Aboolkhairia et al., 2014)</td>
</tr>
<tr>
<td>Scan spacing</td>
<td>Overlapping distance</td>
<td>Microstructure, Thermal induced cracks, Porosity</td>
<td>• Optimum overlaps ensure the material is sufficiently dense, achieves full strength and also affects energy absorption.</td>
<td>(Aboolkhairia et al., 2014)</td>
</tr>
<tr>
<td>Powder particle shape</td>
<td></td>
<td></td>
<td>• These impact light absorption and the heat transfer between the particles</td>
<td>(Aboolkhairia et al., 2014)</td>
</tr>
</tbody>
</table>

Table 1: Effect of parameter level on laser-material interaction in LPBF process.
signatures captured by the sensors, which would make any algorithm developed for in-situ monitoring for a particular material non-reusable for another material with confidence. The present work is a feasibility study that focuses on using the idea of Transfer Learning (TL) in Convolutional Neural Networks (CNN). This work aims to demonstrate that the knowledge learned by a CNN from the sensor signatures corresponding to the four mechanisms; 

- Balling, LoF pores, conduction mode and keyhole pores during the processing of stainless steel can be transferred to bronze. In this work, wavelet transforms are used to extract spectrograms which were subsequently used as input to two architectures, namely VGG-16 and ResNets-18.

The paper is organized into five sections: a brief outline of the LPBF process, the mechanisms in the process and the research gaps in-process monitoring are discussed in Section 1. Section 2 gives a brief theoretical basis on the VGG-16, ResNet-18 architecture and Transfer Learning. Section 3 presents the experimental conditions and methodology proposed. Section 4 discusses the transfer learning results on VGG-16 and ResNet-18. Finally, the main contribution of this paper and future works for further optimization of the proposed methodology is discussed in Section 5.

2. Theoretical basis

2.1. VGG-16 and ResNet-18

VGG-16 is one of the state-of-the-art CNN architectures built for object recognition by Oxford’s renowned Visual Geometry Group (VGG) (Simonyan and Zisserman, 2014). The number 16, in this case, indicates the total number of layers involved in building this architecture, as shown schematically in Fig. 1. VGG-16 was one of the first architectures to demonstrate the benefit of increasing the depth of neural nets for better classification accuracy. VGG16 network architecture’s uniqueness is that all convolution layers have only a $3 \times 3$ filter with a stride one and always use a $2 \times 2$ filter of stride 2 for max-pooling layers. Even though it was designed for classifying 1000 categories, it can be used to classify a smaller number of categories (Pandiyan et al., 2019) and sometimes a higher number of categories (Grim et al., 2018). However, due to its numerous fully connected nodes, it is a rather large network, with approximately 138 million parameter weights compared to other networks. The network’s size is the main drawback in terms of its deployment (Alippi et al., 2018) as well as the time required for its training (Qassim et al., 2017). To date, it is still considered to be an excellent pretrained vision model for solving image recognition and segmentation problems (Long et al., 2015). However, Canziani et al. (2016) indicated it could be replaced by more recent advanced and lighter networks such as Inception and Residual Networks (ResNets).

The accuracy of any neural network architecture would saturate, or in worst scenarios, would potentially decrease with the increase in the number of layers. The training of very deep networks is complicated due to the vanishing gradient problem. Indeed, the gradients’ repeated multiplication during the backpropagation results in making the gradient significantly small, which was presented by Huang et al. (2016). To address this issue, He et al. (2015) developed a newer type of architecture to overcome this vanishing gradient problem, namely ResNets. The ResNets employs a shortcut connection skipping the layers to ease the flow of gradients, and it is schematically represented in Fig. 2. The identity skip connection enables the deep networks to go deeper to learn representations with a higher level of abstractions. Canziani et al. (2016) showed that skip connections enable the network to converge faster than plain counterparts such as VGG-16. There are different variants of Resnets; typically, ResNet-18, 34, 50, 101, corresponding to the depth of the layers. Apart from the depth of the layers, the significant difference between these architectures is that, as the layer depth increases beyond 50, the expensive $3 \times 3$ convolution is replaced by $1 \times 1$ convolutions to reduce computation.

2.2. Transfer learning

Traditional machine learning algorithms are trained based on a particular feature space to solve specific tasks. With a change in feature distribution or with the introduction of a new task, the algorithm might fail to adapt. In this case, the algorithm has to be re-trained from scratch. Transfer learning is a paradigm where a model already trained on a similar task is re-used with minimum training to accomplish the second task. With neural architectures built with deep layers, the pretrained weights in them can be re-used with minimum training and usage of computing resources. But, it is also to be noted that transfer learning is handy in deep learning if the features learned by the pre-trained model from the first task are general. Fig. 3 presents different strategies adapted based on the complexity of the second task. In the case of tasks with higher complexity, the whole network is trained from the saved weights, as shown in Fig. 3(a). For a similar task, the few convolution layers or classification layers are trained, as illustrated in Fig. 3(b) and (c). The training time is directly proportional to the number of learnable parameters to be updated during training. Apart from image recognition and segmentation applications, the transfer learning paradigm has also been applied to fault diagnosis in locomotive bearings (Yang et al., 2019), identify remaining useful life prediction of the tool in manufacturing processes (Sun et al., 2018), which prompted us to exploit this technique towards AM.
Fig. 2. Schematics of the ResNet –18 architecture.

Fig. 3. Different strategies in transfer learning based on the problem complexity.
3. Experimental setup and methodology

### 3.1. Experimental setup

A series of LPBF line tracks were produced for two different materials using a customized setup shown in Fig. 4. In this study, two materials with significant differences in mechanical, optical and thermal properties. The first powder is a 316 L stainless steel (MetcoAdd 316L) from Oerlikon Metco, whereas the second material was a bronze (CuSn8) purchased from Heraeus Materials SA (Ghasemi-Tabasi et al., 2020). The chemical composition of the stainless steel and bronze powders are listed in Table 2 and Table 3. The spherical powder particle size distributions and their relative densities are listed in Table 4. The process parameters inducing the four build qualities; balling, LoF pores, condution mode and keyhole pores, are listed in Table 5. From this table, it is seen that two process parameters per condition have been used. The single-line tracks were performed on a defect-free cube built previously with a parallel uni-directional scan strategy with a spacing of 0.1 mm between them. A continuous-wave fiber laser with a 1070 nm wavelength and a spot size of 82 µm (1/e²) at the focal plane with an M² < 1.1 was used. The enclosed process chamber prevented the powder bed from being contaminated during the experiments, and nitrogen was used as the inert gas with a flow rate of 1 m/s. Additional it was ensured that the oxygen content inside the chamber was below 200 ppm, which corresponds to 0.01%.

The four build qualities were simulated on both powders based on the normalized enthalpy calculations as plotted in Fig. 5 and Fig. 6. The normalized enthalpy over the normalized melt pool depth was calculated (Ghasemi-Tabasi et al., 2020) based on Eqs. (1) and (2), where \( \rho \) is the density \(( \text{kg/m}^3 \)), \( \alpha \) is the absorptivity of the bulk material, \( P \) is the laser power (W), \( C \) the specific heat \( (\text{J/kg} \cdot \text{K}) \), \( \Delta T \) the difference between the melting and initial temperature (K), \( L_m \) the latent heat of melting \( (\text{J/kg}) \), \( \omega \) the laser spot radius (m), \( V \) the laser speed \( (\text{m/s}) \), \( D \) the thermal diffusivity \( (\text{m}^2/\text{s}) \), and \( d \) the melt pool depth (m).

\[
\bar{d} = \frac{\Delta H}{\Delta h} = \alpha P \left( \frac{C \Delta T L_m}{\rho \Delta h} \right)^{1/3} \pi \omega V D
\]  

(1)

\[
\bar{d} = \frac{d}{\theta}
\]  

(2)

The work’s primary focus was to evaluate whether the proposed transfer learning strategy can be applied for a larger process space and independent of the process parameters across the materials. As confirmed from Figs. 5 and 6, we can see that two sets of parameters were chosen across mechanisms with different normalized enthalpies covering a larger process space. Again comparing between Figs. 5 and 6, the enthalpies of the mechanisms across stainless steel and bronze are different, confirming that if transfer learning works, it might be independent of the process parameters across materials. Also, to make the classification and transfer learning task a bit trickier, the dataset was prepared by including data corresponding to balling and LoF pores for the two alloys. Laser energy density is considered a critical factor affecting the properties of as-built parts (Gu et al., 2013). Out of the four build qualities studied in this work, three of them, namely balling, LoF pores and keyhole, are unfavourable. The occurrence of balling and LoF pores is the result of a deficit in laser power. On the other hand, porosity caused by keyholes is due to excessive laser power absorbed. However, due to the two materials’ optical reflectivity, the energy required for the same mechanism is higher for bronze than for stainless steel. Lastly, cross-sections perpendicular to the line track is investigated by a light microscope to confirm either the occurrence or absence of defects. Typical optical microscopic images of the different build qualities for stainless steel and bronze are shown in Fig. 5 (stainless steel) and Fig. 6 (bronze).

### 3.2. In situ sensing setup and data processing

An air-borne acoustic emission (AE) sensor PAC AM4I with a working range of 0 – 100 kHz was used to capture the process signatures emitted during line track trials for both materials. The acoustic sensor is a resonant sensor with peak frequencies around 40 and 80 kHz. It is kept in proximity to the build plate at 10 cm, as shown in Fig. 4. The sensor location was fixed for all experiments to ensure repeatability and consistency. The AE signals were captured at a rate of 1 MHz, satisfying the Nyquist Shannon theorem using an Advantech Data Acquisition (DAQ) card. The acquisition of the DAQ card was triggered once the laser hits the powder based on thresholding. The data captured are locally stored for further processing. In this work, 200 line tracks were performed for each material, and the four build qualities resulted in 1600 lines.

The acquired AE signals were sequentially processed, as illustrated in Fig. 7, to obtain spectrograms which were subsequently used as input to the VGG and ResNet architectures. For each set of process parameters, the signals were split into window sizes of 2500 µs. Based on the operating range of the acoustic PAC AM4I sensor, frequencies higher than 100 kHz was removed using a low pass Butter-worth filter. Next, the filtered signal was convoluted with a scaled and translated version of the wavelet to compute the Continuous Wavelet Transform (CWT) coefficients. After an exhaustive search, the Morlet was used as the mother wavelet with a scaling value of 500. The application of Morlet wavelet for feature extraction and analysis has been well established for fault diagnosis in ball bearings (Kankar et al., 2011) and gear-box (Lin and Qu, 2009). The coefficients computed after the transform are converted into a 2D spectrogram of size 512 × 512 pixels. The maximum and minimum limits were computed from the CWT coefficients of all build quality to scale all the spectrogram images. For each material and build quality, 2000 spectrogram images were produced per mechanism. This database is balanced in order to avoid biasing during the CNN training.

### 3.3. Methodology

The proposed methodology for transferring knowledge acquired about different build qualities by a convolutional network from one material to another material is depicted in Fig. 8. First, the network is

![Fig. 4. Experimental setup involving LPBF process.](image)
supervisely trained with labelled spectrogram images from stainless steel for each build condition. It is important to note that the network weights are initially randomized during training. The performance of the network is assessed by comparing the prediction of the network and the corresponding ground truth. Once a reliable accuracy is achieved, indicated by the training accuracy and loss curves reaching a plateau, the training is stopped. Second, the pre-trained model is used as the base model to train the build quality found in another material, in this case, bronze. However, during the training with the second material, the network is not trained from the beginning. Actually, only a part of the network weights is re-trained, as shown in Fig. 8. A part of the knowledge learned by the network from the first material (stainless steel) is preserved, and the new knowledge of the second material (bronze) is augmented. Once a reasonable accuracy is achieved on the second material, the training is stopped. This work trains deep networks such as VGG-16 and ResNet-18 on spectrogram images corresponding to four different build qualities. The trained VGG-16 and ResNet-18 architecture weights are frozen until the last layer, thereby restoring the learned knowledge. Only the last layer weights are allowed to be updated during training with spectrogram images corresponding to bronze. The transfer learning was performed in two modes. In the first mode, the frozen network was trained on the bronze spectrogram dataset with a size similar to the stainless steel training dataset. In the second mode, the bronze dataset was reduced to half (50%) the size of the stainless steel dataset during re-training of the frozen network.

4. Transfer learning using VGG-16 and ResNet-18 architecture

The spectrogram images created, as discussed in Section 3.2, with a resolution of 512 × 512 pixels, is given as input to two types of CNN architectures, namely VGG-16 and ResNet-18. From a dataset of 8000 spectrogram images for each material, 5200 images were stochastically selected for the training and the remaining 2800 images were used for testing. We ensured that the weightage, i.e. the number of spectrogram images of all four build qualities in the train and test datasets, is balanced during this stochastical selection. The VGG-16 and ResNet-18 CNN architectures are trained with a GeForce RTX 2080 Ti Graphical Processing Unit (GPU). The training process of the two CNN architectures was implemented in Pytorch (Paszke et al., 2019). The training parameters for both VGG-16 and ResNet-18 architectures are listed in Table 6. The 200 epochs for training was chosen over an exhaustive search to have a fair comparison across two different architectures and the respective accuracy of the two models. Furthermore, batch normalization was applied across layers in the respective model to ensure that overfitting does not occur. It was also ensured that the datasets were shuffled across epochs, and a dropout of 0.5 was applied during training. Additionally, we have stabilized the training by reducing the learning rate to half after every 25 epochs.

![Fig. 5. Normalized enthalpy of the printed stainless steel samples of different build qualities versus the normalized melt pool depth (Pandiyan et al., 2020).](image-url)
4.1. Transfer learning using VGG –16 Architecture

The Fully Connected (FC) classification layer of the VGG-16 architecture, which typically classify 1000 classes, is modified based on our objective for classifying four build qualities, i.e. balling, LoF pores, conduction mode and keyhole pores. During training with the stainless steel data, the cross-entropy was the loss function on a batch size of 10 for 200 epochs. After every epoch, the model with updated weights is tested against the test dataset consisting of 2800 images. During the entire training process of the VGG-16 network, the ≈ 134 million

Fig. 6. Normalized enthalpy of the printed bronze samples of different build qualities versus the normalized melt pool depth.

Fig. 7. Workflow to build the spectrogram dataset from line track experiments.
parameter weights were updated. The learning rate was initialized at 0.001 and halved after every 25 epochs. Fig. 9 shows the accuracy and loss curves for the VGG-16 model trained on the spectrogram images. It is seen that the accuracy increases and the loss decreases with every epoch, confirming that the network learns patterns during the training process. The classification accuracy of the trained VGG-16 on the test dataset is shown in the confusion matrix in Table 7. In this table, trained VGG-16 model prediction of built qualities (balling, LoF pores, conduction mode and keyhole pores) (in rows) versus the ground truth (in columns) using the parameters listed in Table 6 after 200 epochs are given. The classification accuracies in the table are defined as the number of true positives divided by the total number of tests for each category. These values are given in the diagonal cells of the table (dark grey cells). The classification errors are computed as the number of the true negatives divided by the total number of the tests for each category. These corresponding values are filled in non-diagonal row cells. After 200 epochs, using the training parameters listed in Table 6, the trained VGG-16 model achieves an accuracy of $\approx 96\%$ for classifying the four build qualities. The model training on the GPU listed in lasted for 18 h.

For the transfer learning, the weights of the VGG-16 model trained on classifying the stainless steel build qualities are frozen except the FC layer, as shown in Fig. 10. The weights in the FC layer get updated during the transfer learning of the pre-trained VGG-16 network with the bronze spectrogram dataset. During the transfer learning of the pre-
trained VGG-16 network with the bronze dataset, about ≈ 119 million weight parameters get updated, whereas ≈ 15 million weight parameters from the convolutions layers have learned the patterns are frozen. The transfer learning was executed in two modes. First, training the freezed network with the bronze spectrogram dataset with a size similar to the stainless steel training dataset (8000 images). Second, by reducing the bronze dataset to half (4000 images).

The training parameters used during the transfer learning of the pre-trained VGG-16 are listed in Table 6. Fig. 11 shows the accuracy and loss curves during transfer learning on the full bronze dataset. Comparing loss curves between Fig. 9 and Fig. 11, it is evident that the loss values are more stable during the base VGG-16 network training process than during the transfer learning.

The classification accuracy of the VGG-16 model from the transfer learning on the full bronze test dataset is given in the confusion matrix in Table 8 (a). After 200 epochs computed in 9 h, the VGG-16 model from the transfer learning reached an average accuracy of ≈ 85%. Misclassification was found between two mechanisms, such as LoF pores and conduction mode. For transfer learning in the second mode, where the freezed VGG-16 network is trained with the bronze dataset, which is 50% in size of the stainless steel dataset, an accuracy of ≈ 82% was achieved, and evidence of this is in Table 8 (b). The transfer learning in the second mode lasted for 6 h for 200 epochs. The training times were considerably reduced two-fold during the transfer learning of the VGG-16 model in the first mode and threefold in the second mode.

### 4.2. Transfer learning using ResNet - 18 Architecture

Similar to the training of the VGG-16 network, the ResNet-18 architecture was also trained using the parameters listed in Table 6 on the spectrogram dataset from stainless-steel line track experiments. Fig. 12 shows the accuracy and loss curves increasing and decreasing with every epoch, confirming that network weights adapt to classify the build quality. During the entire training process with a batch size of 40, about ≈ 11 million parameter weights of ResNet-18 architecture were updated using backpropagation. As indicated in the confusion matrix in Table 9, the trained ResNet-18 model was able to classify with an overall

![Fig. 10. Freezing weights of the pretrained VGG-16 for transfer learning.](image-url)
accuracy of \( \approx 94\% \) after 12 h of training.

For the transfer learning of the pre-trained ResNet-18 model, only the fifth bottleneck block layer and FC layer’s weight is trainable, as shown in Fig. 13. The knowledge and patterns learned by the ResNet-18 network during the previous training on the stainless steel dataset are preserved as those weights are frozen. Out of \( \approx 11 \) million parameter weights, only \( \approx 8 \) million parameter weights are updated via backpropagation during transfer learning. The training parameters listed in Table 6 are used for transfer learning. Similar to VGG-16, the transfer learning on the Resnet – 18 architecture was also performed in two modes. Fig. 14 shows the accuracy and loss curves during the transfer learning using the ResNet architecture on the full bronze dataset. Unlike VGG-16, the loss curves for the ResNet-18 during transfer learning and regular learning are stable. The transfer learned ResNet-18

<table>
<thead>
<tr>
<th></th>
<th>Balling</th>
<th>LoF pores</th>
<th>Conduction mode</th>
<th>Keyhole pores</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ground truth</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Classification accuracy ( % )</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Balling</td>
<td>94.0</td>
<td>3.50</td>
<td>2.50</td>
<td>0</td>
</tr>
<tr>
<td>LoF pores</td>
<td>2.0</td>
<td>76.5</td>
<td>21.0</td>
<td>0.50</td>
</tr>
<tr>
<td>Conduction mode</td>
<td>3.0</td>
<td>17.75</td>
<td>75.75</td>
<td>4.0</td>
</tr>
<tr>
<td>Keyhole pores</td>
<td>0</td>
<td>1.5</td>
<td>5.0</td>
<td>93.5</td>
</tr>
</tbody>
</table>

Fig. 11. Accuracy and training loss plots during transfer learning of pretrained VGG-16 model on bronze spectrogram dataset.

Table 8
Classification accuracy of the VGG-16 model via transfer leaning for mechanisms occurring during the LPBF process of bronze a) Full dataset b) 50% of the dataset.

<table>
<thead>
<tr>
<th></th>
<th>a) Full dataset (Mode I)</th>
<th>b) 50% of the dataset (Mode II)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ground truth</td>
<td></td>
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<td>Classification accuracy ( % )</td>
<td>Balling</td>
<td>LoF pores</td>
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<tr>
<td>Balling</td>
<td>94.0</td>
<td>3.50</td>
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<tr>
<td>LoF pores</td>
<td>2.0</td>
<td>76.5</td>
</tr>
<tr>
<td>Conduction mode</td>
<td>3.0</td>
<td>17.75</td>
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<tr>
<td>Keyhole pores</td>
<td>0</td>
<td>1.5</td>
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<th>a) Full dataset (Mode I)</th>
<th>b) 50% of the dataset (Mode II)</th>
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Fig. 12. Accuracy and training loss plots during the training of ResNet-18 model on stainless-steel spectrogram dataset.
model achieves an overall accuracy of \( \approx 87\% \) in the first mode as shown in the confusion matrix in Table 10 (a). When training the network with the bronze dataset, which is 50% in size of the stainless steel data set, the freezed ResNet-18 model from the transfer learning still reaches an overall accuracy of \( \approx 84\% \), and evidence of this is in Table 10 (b). The training times were considerably reduced by 6 h in the first mode and 4 h in the second mode during transfer learning of the ResNet-18 model.

Based on both CNN architectures’ prediction results, we demonstrated that with spectrograms images as input, the material build qualities commonly occurring in additive manufacturing such as balling, LoF pores, conduction mode and keyhole pores could be classified on original materials. Secondly, with transfer learning, the qualities in another material could be predicted with the patterns and knowledge trained with build qualities in a first material. Comparing two CNN architectures used in this study, the ResNet-18 performs better in transfer learning with only \( \approx 11 \) million parameter weights as compared to VGG-16 (\( \approx 134 \) million parameter weights) for the two transfer learning modes. Finally, we demonstrated that the transfer learning technique is very advantageous from an industrial perspective in terms of minimum training time and dataset collection when transferring the knowledge from one material to another in processing Functionally Graded Materials (FGM) or multi-materials. In this study, the training times were also considerably reduced by three-fold and two-fold in the two modes during transfer learning for Resnet-18 and VGG-16 models, respectively.

### 4.3. Comparison of VGG-16 and ResNet - 18 without transfer learning

A comparative study was also performed to understand the performance of the models trained from scratch and using transfer learning on the bronze dataset. For training of the two models, namely VGG-16 and

![Fig. 13. Freezing weights of pretrained ResNet-18 for transfer learning.](image)

![Fig. 14. Accuracy and training loss plots during transfer learning of pretrained ResNet-18 model on bronze spectrogram dataset.](image)
ResNet-18, from scratch, the training parameters listed in Table 6 were used. As indicated in the confusion matrix in Table 11(a), the trained VGG-16 was able to classify with an overall accuracy of $\approx 91\%$ after 18 h of training. For the case of the trained ResNet – 18, the classification accuracy was $\approx 89\%$ after 12 h, and evidence of this is in the confusion matrix in Table 11(b). In terms of classification accuracy, the two models trained from scratch were higher on the full bronze dataset as compared to the one using transfer learning. However, in the case of training time, as previously known, models trained using transfer learning took only half of the time required to train the model from scratch.

5. Conclusion

In this contribution, we have investigated a novel method for classifying four build qualities such as balling, LoF pores, conduction mode and keyhole pores occurring during the LPBF process across two materials. When processing line track experiments, the AE signals were recorded using a microphone that had an operating range of 0–100 kHz. From the AE signals, spectrograms images were computed using wavelet transforms with Morlet as the mother wavelet for a window size of 2500 $\mu$s. The spectrogram-based classification was performed in two different materials: stainless steel (316L) and bronze (CuSn8). Instead of training the network from scratch to classify the four qualities occurring in bronze, we have proposed a transfer learning technique using pretrained models from the stainless steel data as an alternate methodology. The methodology has been applied to state-of-the-art CNN architectures, namely VGG-16 and ResNet-18, to explore the interest of transfer learning on additive manufacturing. Moreover, transfer learning was applied to these two architectures in two modes: The bronze training dataset size was similar to the stainless steel original dataset in the first mode. The bronze training dataset size was 50% of the stainless steel original dataset in the second mode. The following generalized conclusions can be drawn based on the experimental results:

- The VGG-16 network outperforms the ResNet-18 network slightly in terms of accuracy in classifying the build quality from line track stainless steel experiments. However, taking the size of the network into account, the improved performance of the ResNet-18 network with $\approx 11$ million trainable parameters versus VGG-16 with $\approx 134$ million trainable parameters is commendable.
- The ResNet-18 outperforms VGG-16 during the classifications of the build quality in the bronze during the transfer learning in both modes. For the two modes, the transfer learning of VGG-16 had an overall classification accuracy of 85% and 82%, respectively. In contrast, the Resnet-18 model had overall classification accuracy of 87% and 84%. Despite the ResNet-18 network’s small size compared to VGG-16, it outperformed with a better classification accuracy, especially in the second mode of transfer learning.
- Apart from accuracy, the computational times were reduced twofold in the first mode and threefold in the second mode during transfer learning of Resnet-18 and VGG-16 models.

The proposed approach asserts that the knowledge of LPBF processes acquired from one material can be used and further augmented to assess other materials with minimum effort. This work proposes to work on 2D...
spectrogram image input on two native architectures; however, transfer learning can also be performed on simpler architectures with 1D convolutions. Only four build qualities resulting from LPBF processing are studied in this research work, using transfer learning. Transfer learning of mechanisms such as delamination, crack propagation, microstructure formation among various material combinations across machines is also under investigation. The direction towards optimizing hyperparameters for these networks will increase accuracy and optimize training, which is a part of future work. It is to be noted that appropriate sensing techniques capable of capturing these mechanisms are also to be optimized and is a study in progress. Though the proposed strategy is promising for AM process monitoring, there is an inherent disadvantage of such a technique as they unload some of the previously gained knowledge acquired on one material when re-trained on another. In other words, these models are specific to the material composition and cannot be generalized. Also, the complexity of the CNN model required for monitoring may not be homogeneous when processing all the materials, therefore in some cases complex model may be applied on trivial tasks. The data and codes for this work are present in the following repo (https://c4science.ch/diffusion/11778/).

CRediT authorship contribution statement


Declaration of Competing Interest

The authors declare that there have been no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The author would like to acknowledge the financial support of the project MoCont from the program of the Strategic Focus Area Advanced Manufacturing (SFA-AM), a strategic initiative of the ETH Board. RDD and RL gratefully acknowledge the generous sponsoring of PX Group to their laboratory.

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