Deep Learning-Based Quality Inspection in Additive Manufacturing

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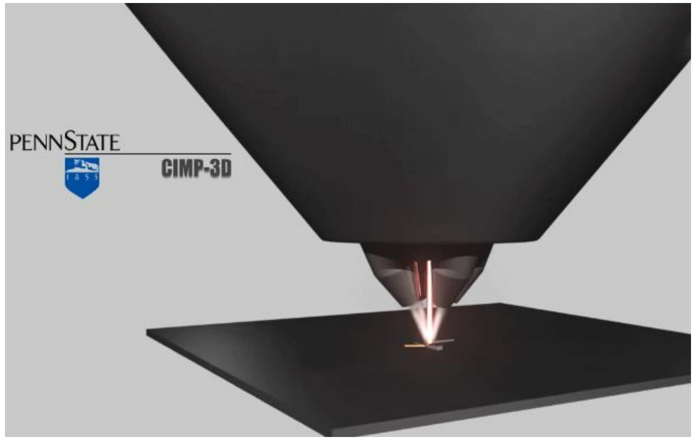
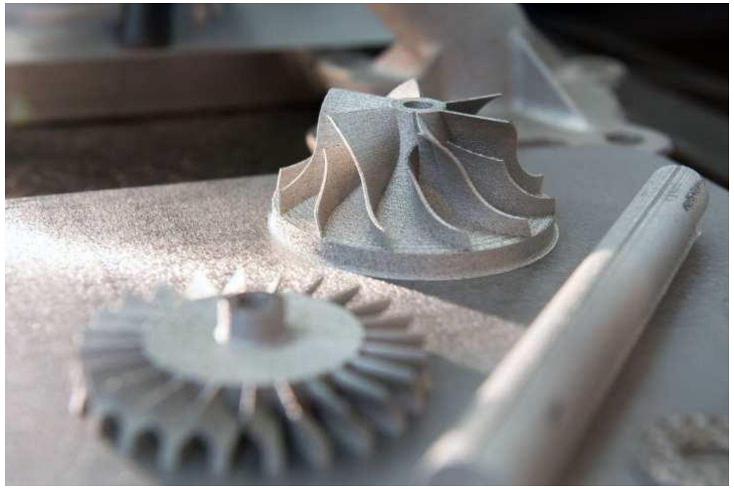
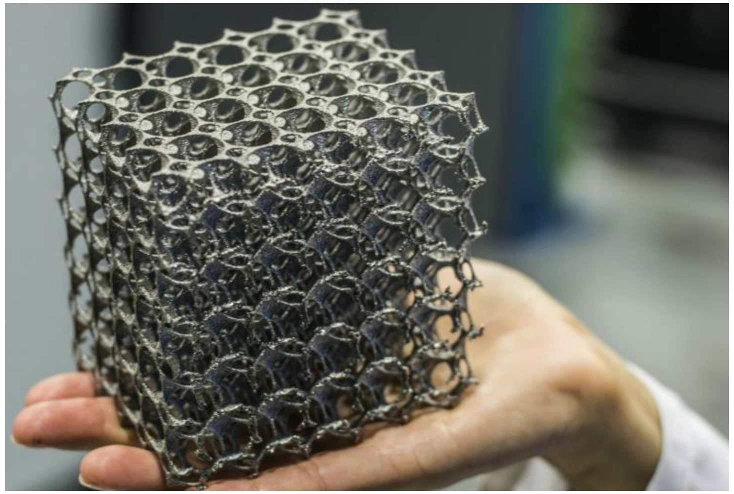
Additive Manufacturing

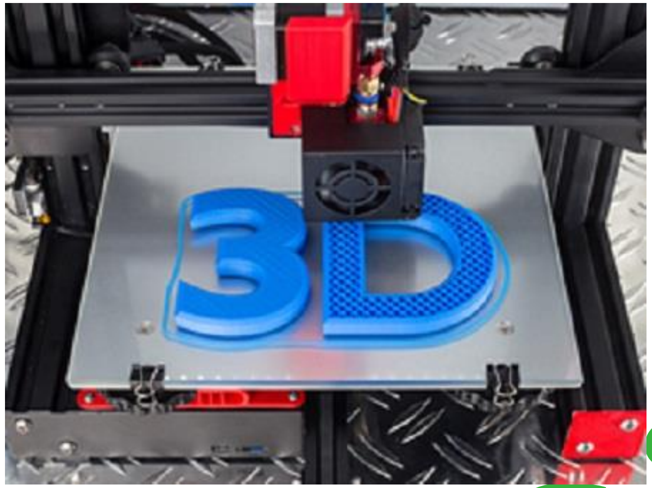
Laser metal deposition (LMD) process

- **Layer-by-layer fabrication**
- **Powder feedstock**
- **Dissimilar materials welding**









Additive Manufacturing

AM market

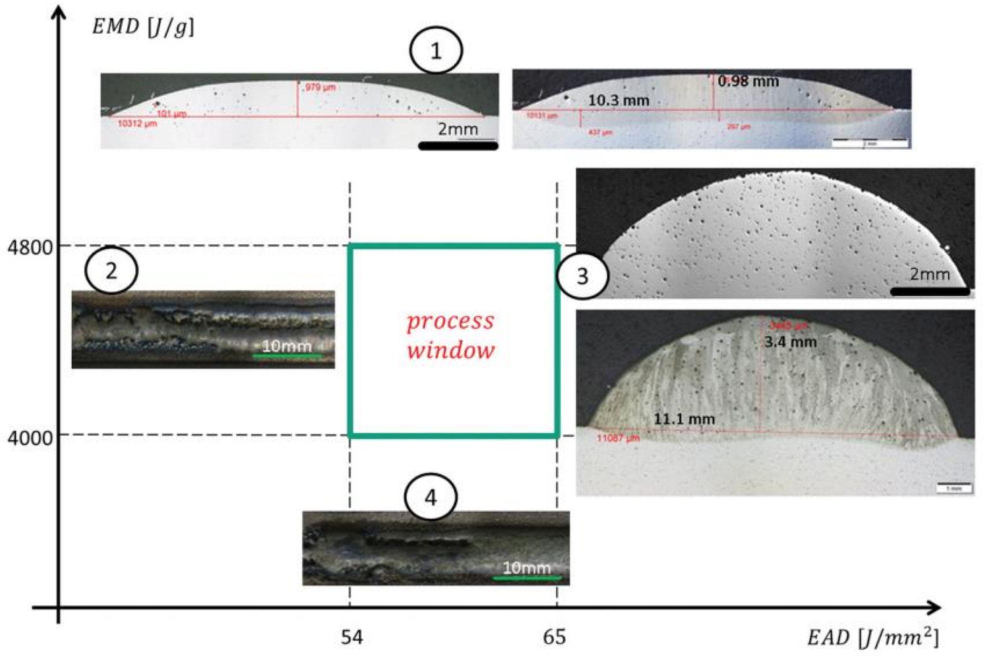
- **$21.5 B revenue in 2025 (Frost & Sullivan)**

Variability of AM process

- **Laser power, scan speed, powder feed rate, beam size**

Typical defects

- **Crack, gas porosity, lack of fusion**

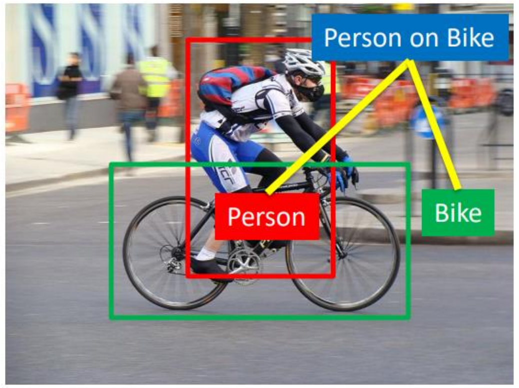


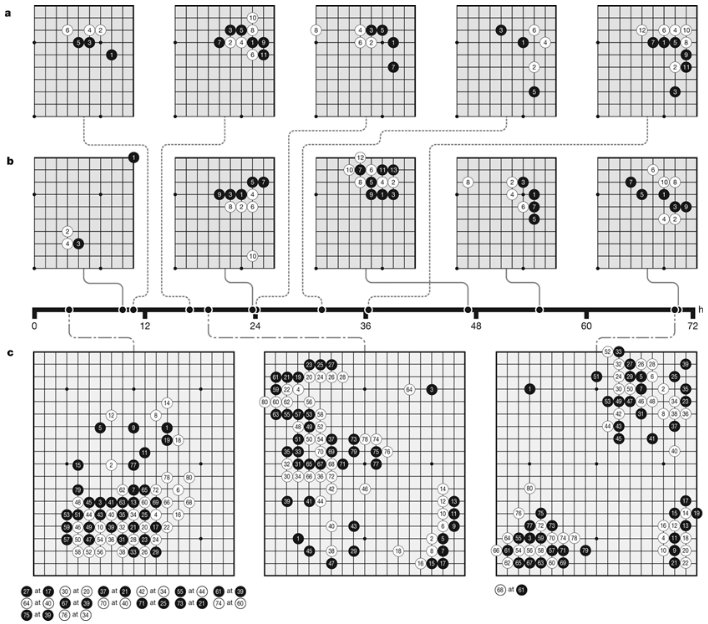
LMD process window, *energy mass density* vs. *energy area density*

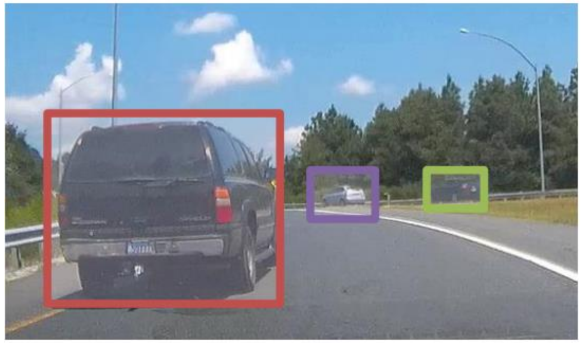
Deep Learning-based Method

Neural network

- **Massive datasets available**
- **Strong computation power**
- **Sophisticated algorithm architecture**







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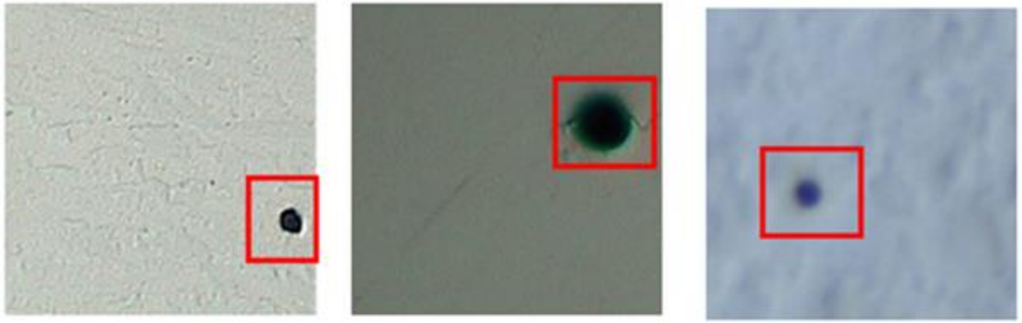
Dataset

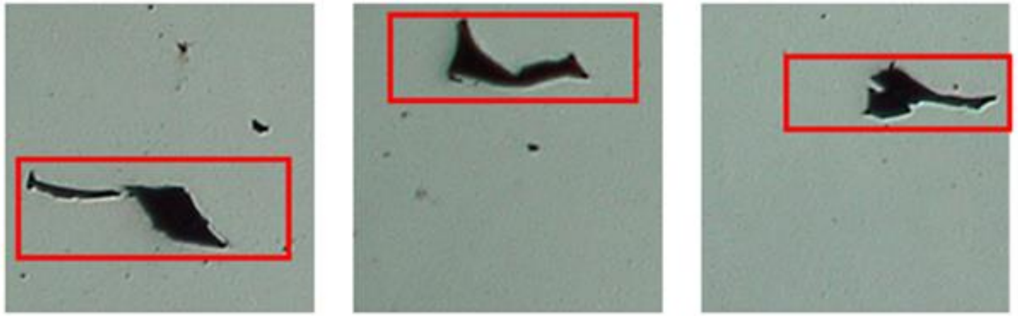
Samples fabricated by LMD at Missouri S&T

- **AISI 304 stainless steel, Ti6Al4V, Inconel 718 alloy, AlCoCrFeNi HEA**
- **Prepared by standard metallurgical procedure**
- **Image size of 224 × 224 pixels**

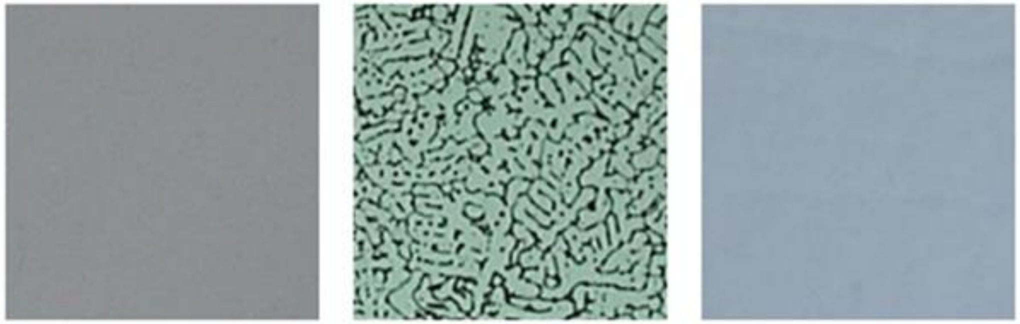
Crack (1013)



Gas porosity (1015)

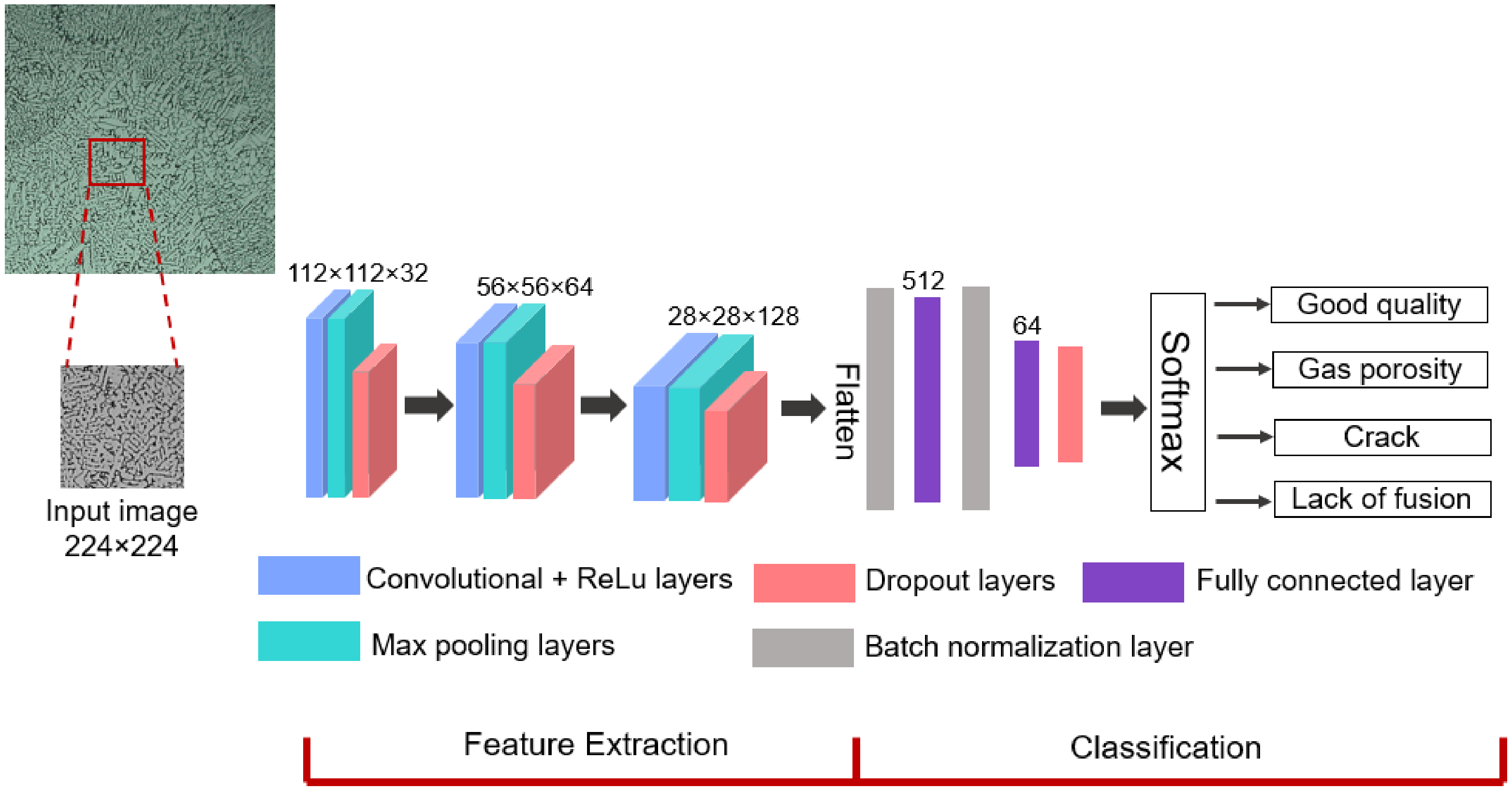


Lack of fusion (1005)



Good quality (1107)

Convolutional Neural Network Architecture



Softmax function:

$$P(y_m = c|X_m) = \frac{\exp(V_c)}{\sum_{c=1}^{C}\exp(V_c)}$$

Cross-Entropy Loss function:

$$L(\omega) = \sum_{m=1}^{M}\sum_{c=1}^{C} \bar{y}_{mc} \log(P(y_m = c|X_m))$$

where $P(y_m = c|X_m)$ is the predicted probability of a sample X_m being class c.

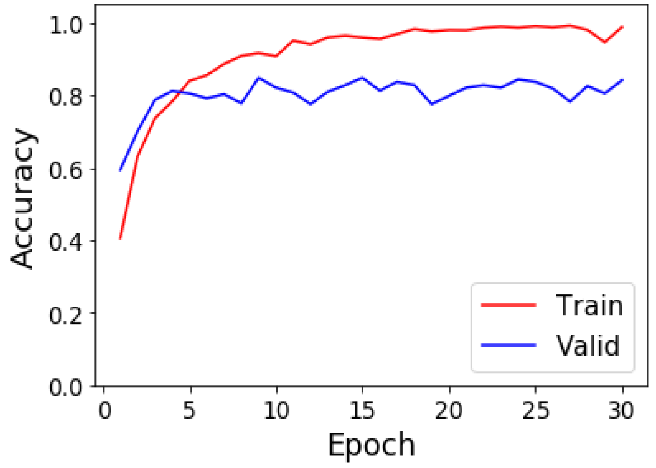
Evaluation of CNN Architecture

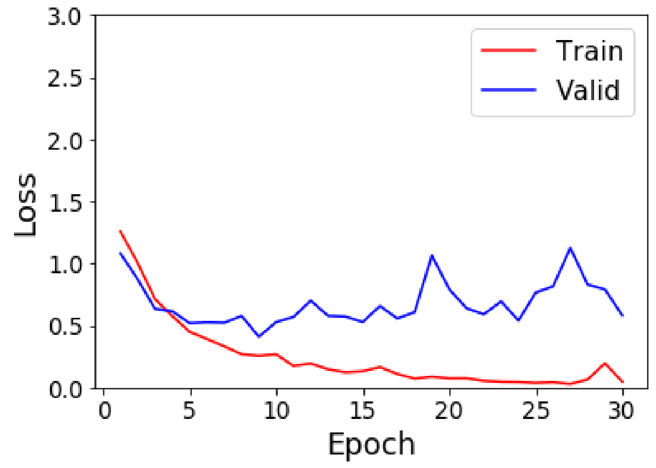
Six representative CNN models

- **Increasing number of conv. Layers**
- **Val. accuracy improves from 74.6% to 83.8%**
- **Overfitting**

Epoch = 30, learning rate = 1e-4

Model #	Architecture	Time (h:m:s)	Val. Acc.%
1	C 3×3/8, C 3×3/16, FC 64	0:4:30	74.6
2	C 5×5/8, C 5×5/16, FC 64	0:4:46	76.7
3	C 3×3/16, C 3×3/32, C 3×3/64, FC 256, FC 64	0:4:37	79.5
4	C 5×5/16, C 5×5/32, C 5×5/64, FC 256, FC 64	0:4:45	80.1
5	C 3×3/32, C 3×3/64, C 3×3/128, FC 512, FC 64	0:5:43	82.5
6	C 5×5/32, C 5×5/64, C 5×5/128, FC 512, FC 64	0:6:31	83.8

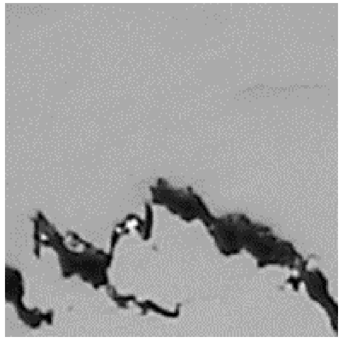


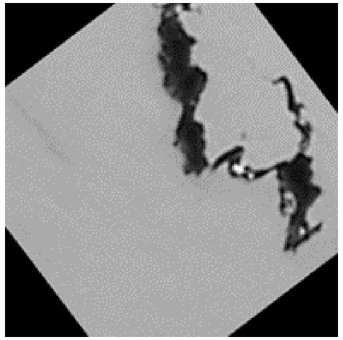


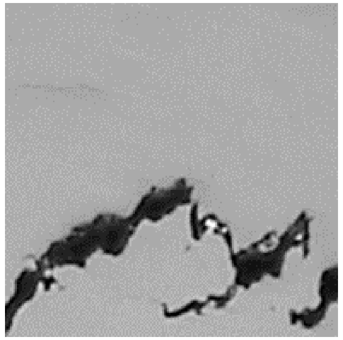
Model 6

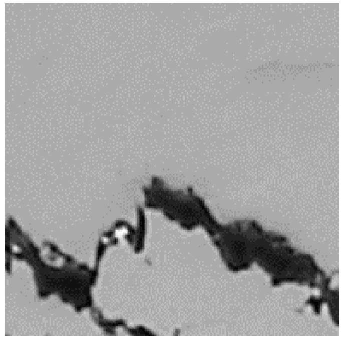
Impact of Data Augmentation

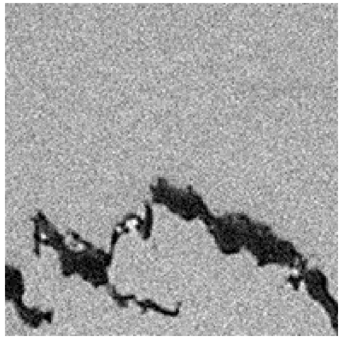
- **Val. accuracy improve up to 5.6%**
- **Takes 5 minutes 13 seconds longer for training**

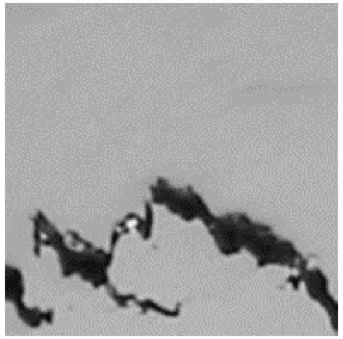

Origin image


Rotation


Horizontal flipping


Random crop


Adding Gaussian noise


Adding blur

Epoch = 30, learning rate = 1e-4

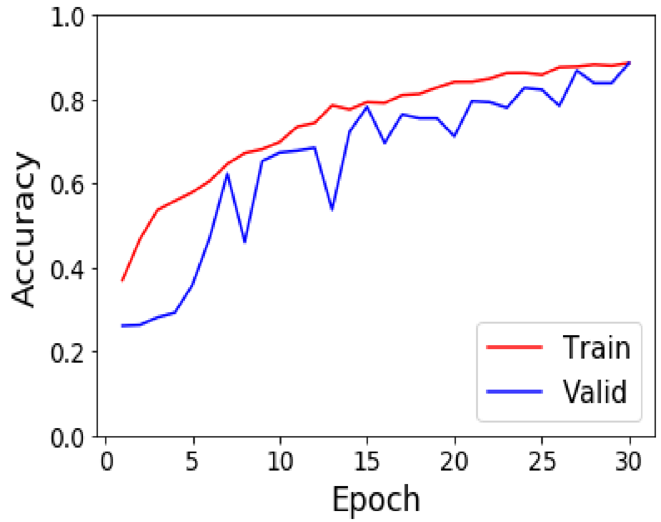
Model #	Time (h:m:s)	Val. Acc.%
3	0:10:39	81.2
4	0:10:11	85.7
5	0:10:37	86.7
6	0:11:05	87.3

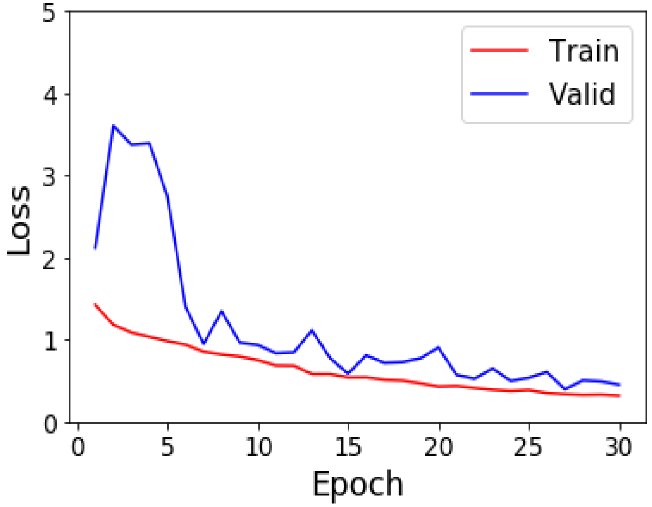
Regularization

- L2 regularization: apply a weight penalty
- Dropout: randomly drop units

Epoch = 30, learning rate = 1e-4

Model #	Architecture	L2	Dropout	Time (h:m:s)	Val. Acc. (%)
7	C 3×3/32, C 3×3/64, C 3×3/128, FC 512, FC 64	Y(1e-5)|N	Y(0.25)|Y(0.25)	0:10:43	84.4
8		Y(1e-5)|Y(1e-5)	Y(0.25)|Y(0.25)	0:11:05	82.5
9		Y(1e-5)|Y(1e-5)	N|N	0:10:47	77.6
10		N|N	Y(0.25)|Y(0.25)	0:10:56	81.2
11	C 5×5/32, C 5×5/64, C 5×5/128, FC 512, FC 64	Y(1e-5)|N	Y(0.25)|Y(0.25)	0:10:24	88.7
12		Y(1e-5)|Y(1e-5)	Y(0.25)|Y(0.25)	0:10:29	87.5
13		Y(1e-5)|Y(1e-5)	N|N	0:10:17	73.2
14		N|N	Y(0.25)|Y(0.25)	0:10:10	87.8

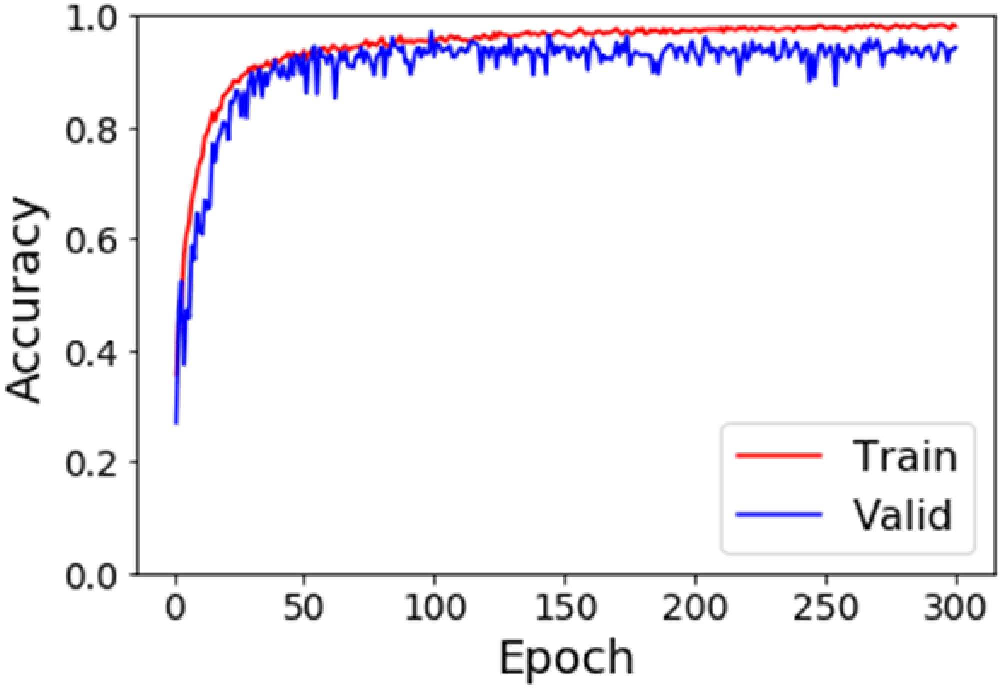


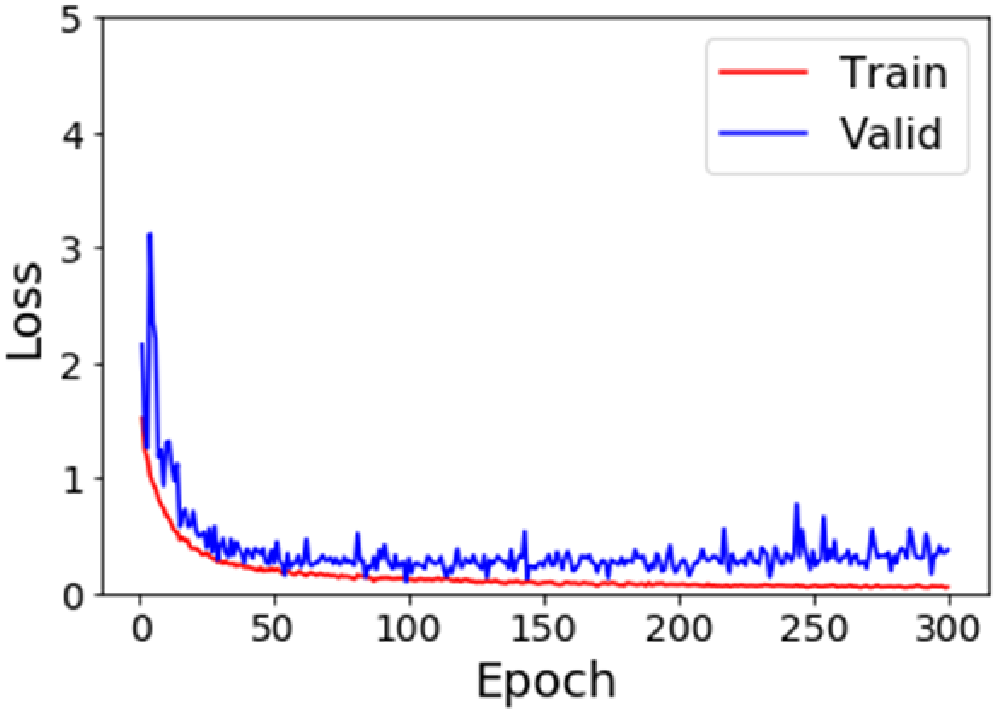


Model 11

Fine Tuning

Epoch = 300, learning rate = 1e-4





Dropout: Y(0.25)|Y(0.25), time:1 h 46 m, val. accuracy=94.3%

Architecture

- C 5×5/32, C 5×5/64, C 5×5/128, FC 512, FC 64

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Performance Evaluation

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = TP/(FN + TP)$$

$$F\ score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

True positive (TP); False positive (FP); False negative (FN)

Class	Precision	Recall	F Score
Crack	0.94	0.95	0.945
Gas porosity	0.91	0.87	0.891
Good quality	0.96	0.94	0.949
Lack of fusion	0.88	0.92	0.901

- Accuracy : 92.1%
- Detection time: 8.01 milliseconds

Alloys	Good	Lack of Fusion	Crack	Gas Porosity
AlCoCrFeNi alloy	93.1%	91.2%	94.9%	88.5%
Ti-6Al-4V	95.1%	88.7%	93.7%	88.3%
AISI 304 stainless steel	96.4%	89.3%	94.8%	90.4%

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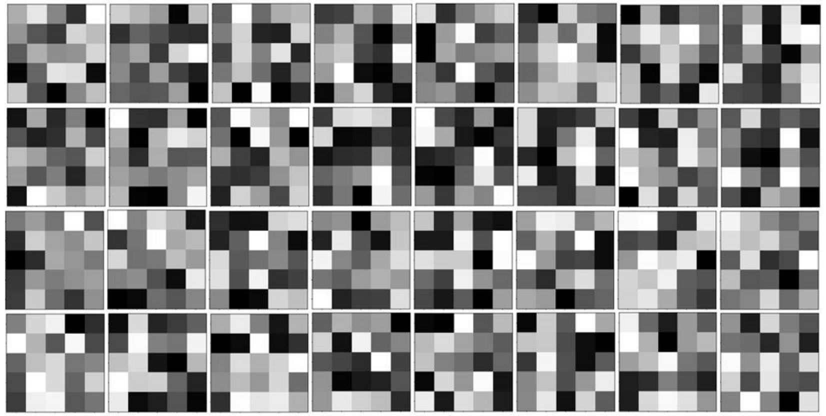
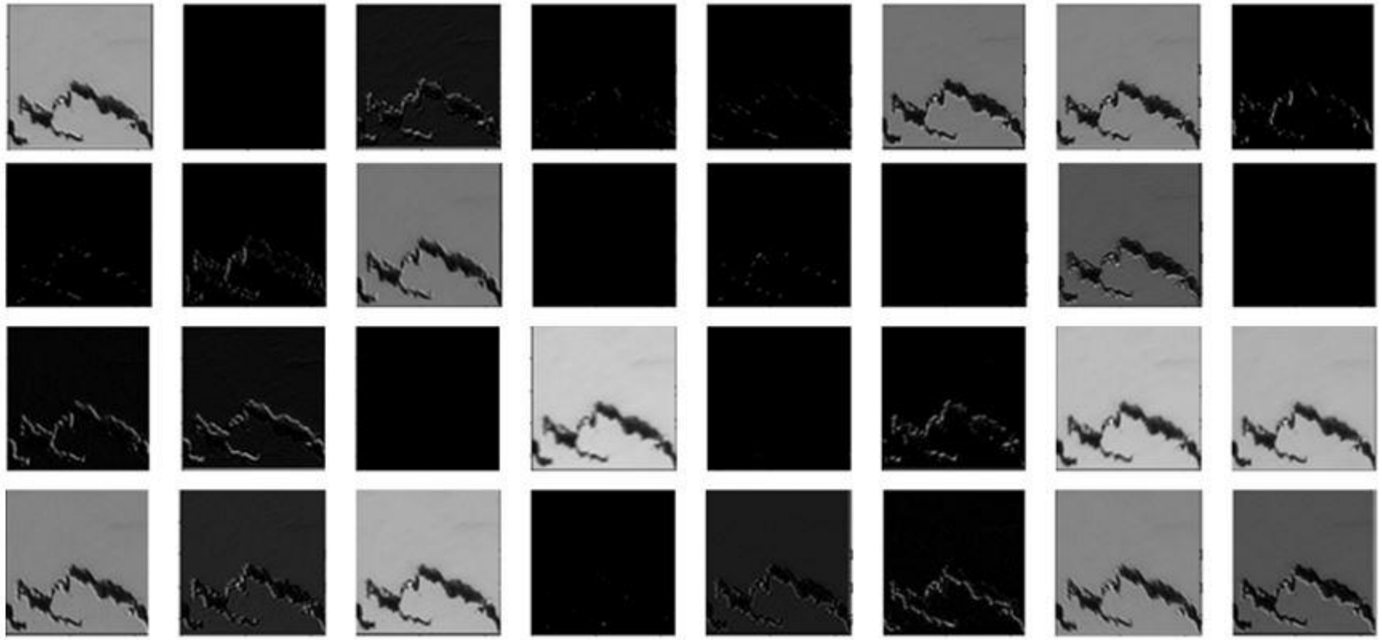
Feature Visualization



32 learned filters of the 1st conv. layer

Crack

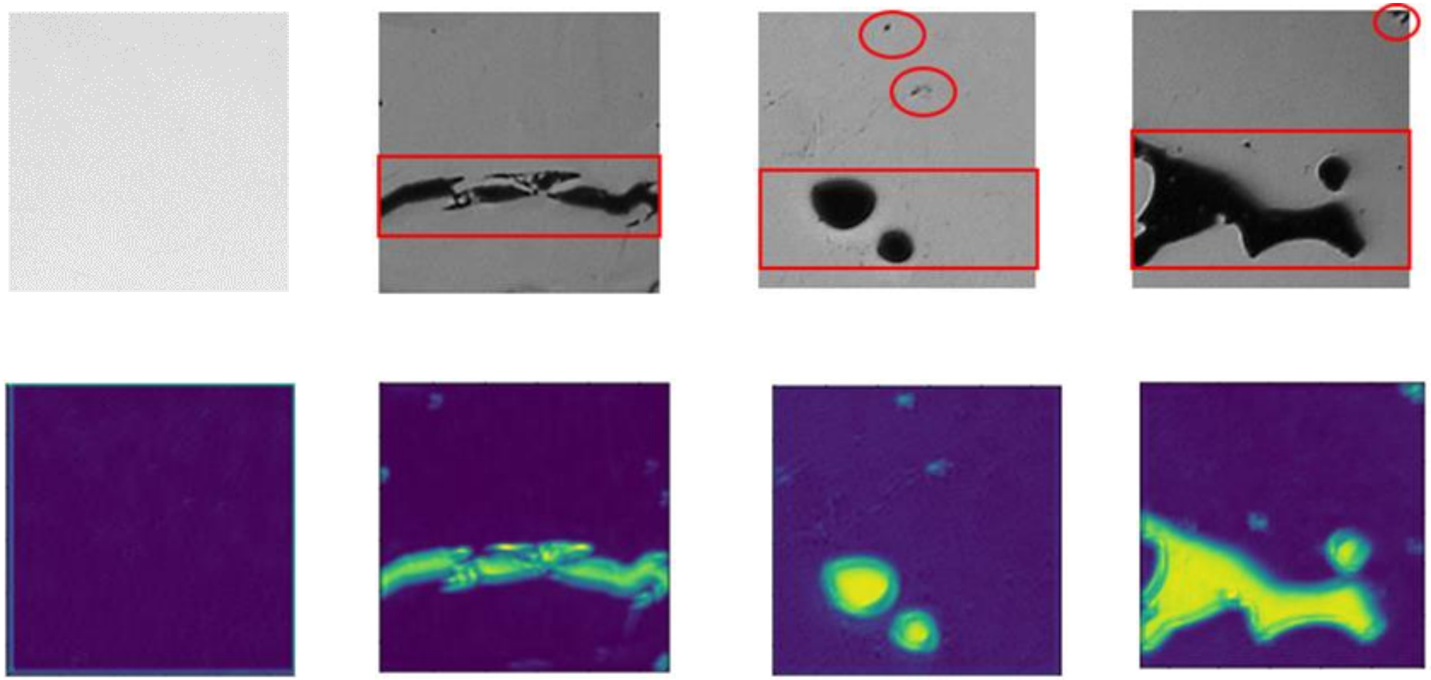


Feature maps

Feature Visualization

Attention maps

- **Obtain through a back-propagation method**
- **Reveal which part of the AM build parts attracts the network's attention**



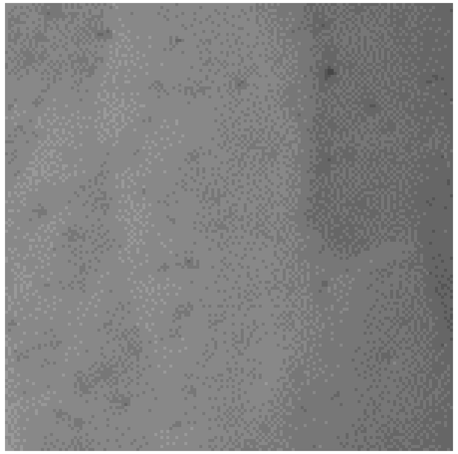
AM build parts

Attention maps

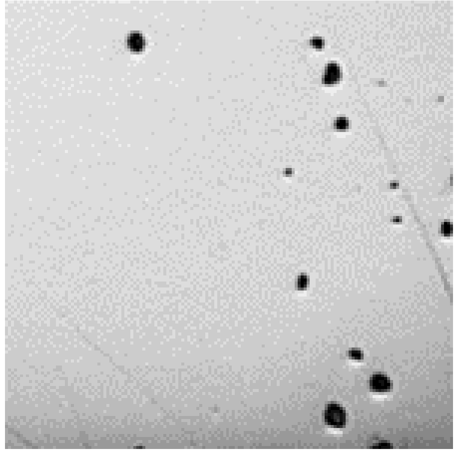
Failure Case Study

Misclassification

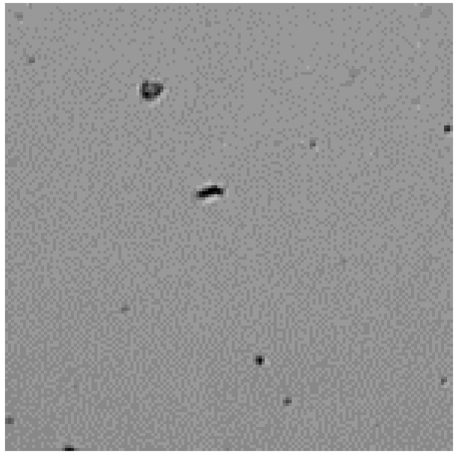
- **Black: correct, red: incorrect classification**
- **High similarity between the gas porosity and lack of fusion**



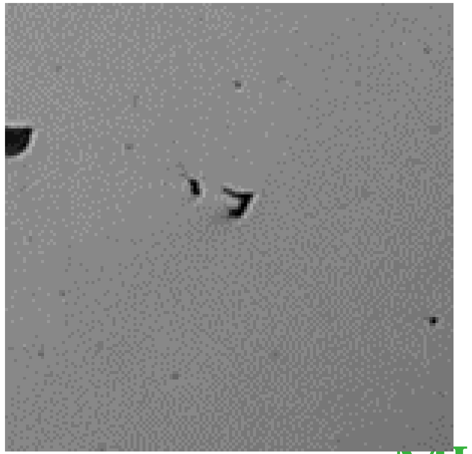
Gas - Good



Gas - LoF



Gas - LoF



LoF – Gas

Conclusions

Development of a neural network towards anomaly detection

- Tradition inspection relies on manual recognition, bias and time-consuming
- A convolutional neural network was developed to detect the four types of defects in additive manufactured products. With the data augmentation and regularization strategies, the detection accuracy improved from 74% to 92%, with 8 milliseconds recognition time of a single piece