

Supplementary Information

Hatch Spacing and Powder Layer Thickness

The printability maps can be further assessed to show the effects of powder layer thickness and hatch spacing. Printability maps were produced for $\text{Ni}_{50.3}\text{Ti}_{49.7}$ with the optimal criteria set. As shown in Supplementary Figure 1, the hatch spacing varied from 75 μm to 90 μm and the powder layer thickness varied from 35 μm to 40 μm . The defect regions change with hatch spacing and powder layer thickness.

As the powder layer thickness and hatch spacing increase, the area for the lack-of-fusion region also increases. The increase in the lack-of-fusion region can be attributed to the fact that the criterion of Equation 4 requires values for hatch spacing and powder layer thickness as inputs. As hatch spacing increases, there is an inadequate overlapping of the melt tracks. Since the join between adjacent tracks and prior layers is insufficient, lack-of-fusion-induced porosity can occur. Furthermore, with increasing powder layer thickness, more energy input (i.e., higher laser power) is required to bond the previous layer or fully bond the melt pool to the substrate. Therefore, both parameters increase the area for the lack-of-fusion region in the printability map.

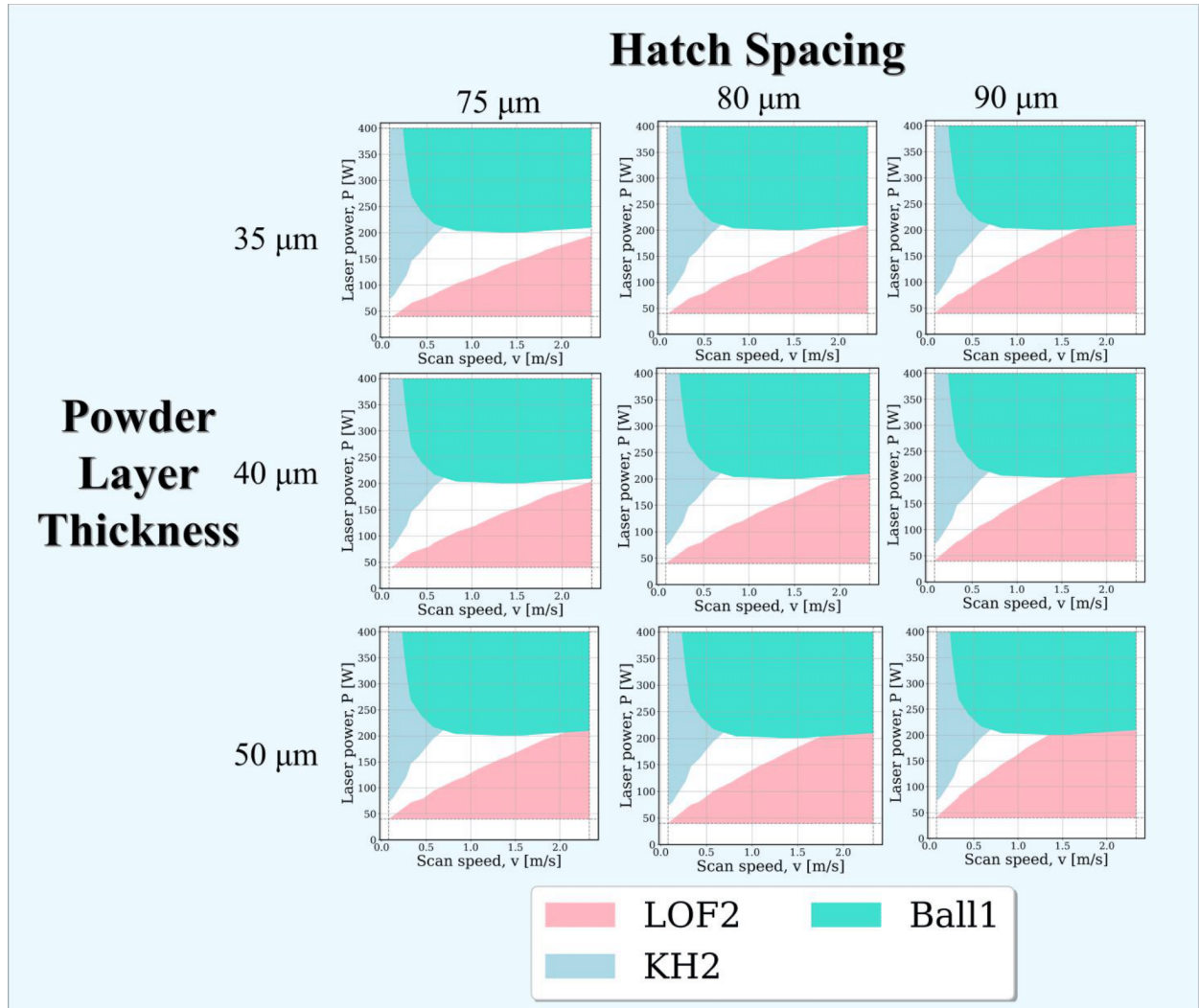
However, there is a need for a formulation or criterion that can visualize the effect of hatch spacing and powder layer thickness on other defect regions, such as keyholing.

Supplementary Table 1 is provided from the main text as a guide into the abbreviations for the criteria combinations for the printability maps.

In addition, Supplementary Table 2 is also provided from the main text to provide an overview of the experimental points used to validate all maps for Inconel 718, Ti-6Al-4V, 316 Stainless Steel, AF96 and Ni-5Nb alloys. The experimental points for the NiTi alloys used to validate the framework are obtained from experiments conducted at Texas A&M University, as discussed in Section 2.2.2.

Defect Type	Label	Equation
Lack-of-Fusion	LOF1	$D \leq t$
	LOF2	$(\frac{h}{W})^2 + \frac{t}{t+D} \geq 1$
Balling	Ball1	$\frac{L}{W} \geq 2.3$
	Ball2	$\frac{\pi W}{L} < \sqrt{\frac{2}{3}}$
Keyholing	KH1	$\frac{W}{D} \leq 2.75$ (for general AM alloys)
		$\frac{W}{D} \leq 2.0$ (for NiTi-based alloys)
	KH2	$\frac{\Delta H}{h_s} = \frac{AP}{\pi h_s \sqrt{\alpha v a^3}} > \frac{\pi T_{boiling}}{T_{liquidus}}$
	KH3	$Ke = \frac{\eta P}{(T_{liquidus} - T_0) \pi \rho C_p \sqrt{\alpha v r_0^3}} > 6$

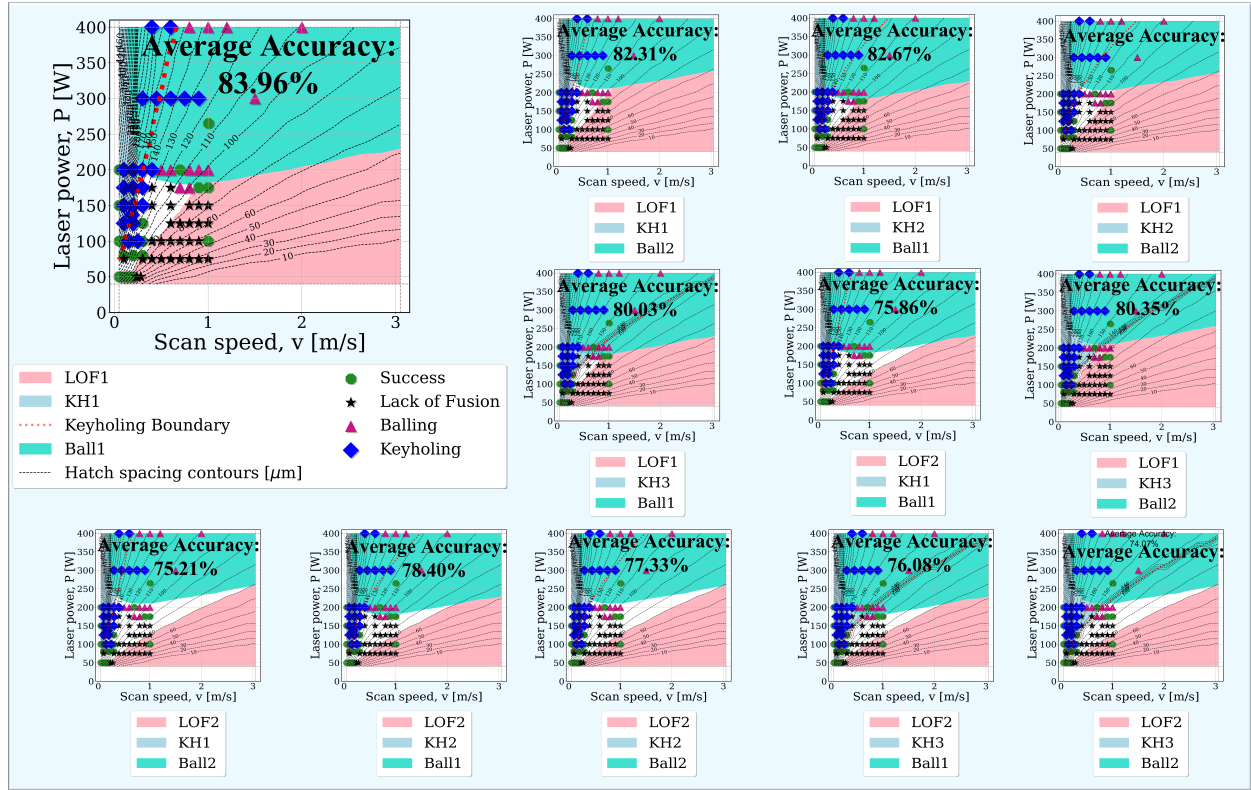
Supplementary Table 1: The equation and labels for each respective defect criteria. A total of 12 printability maps can be generated with every combination of these defect criteria.



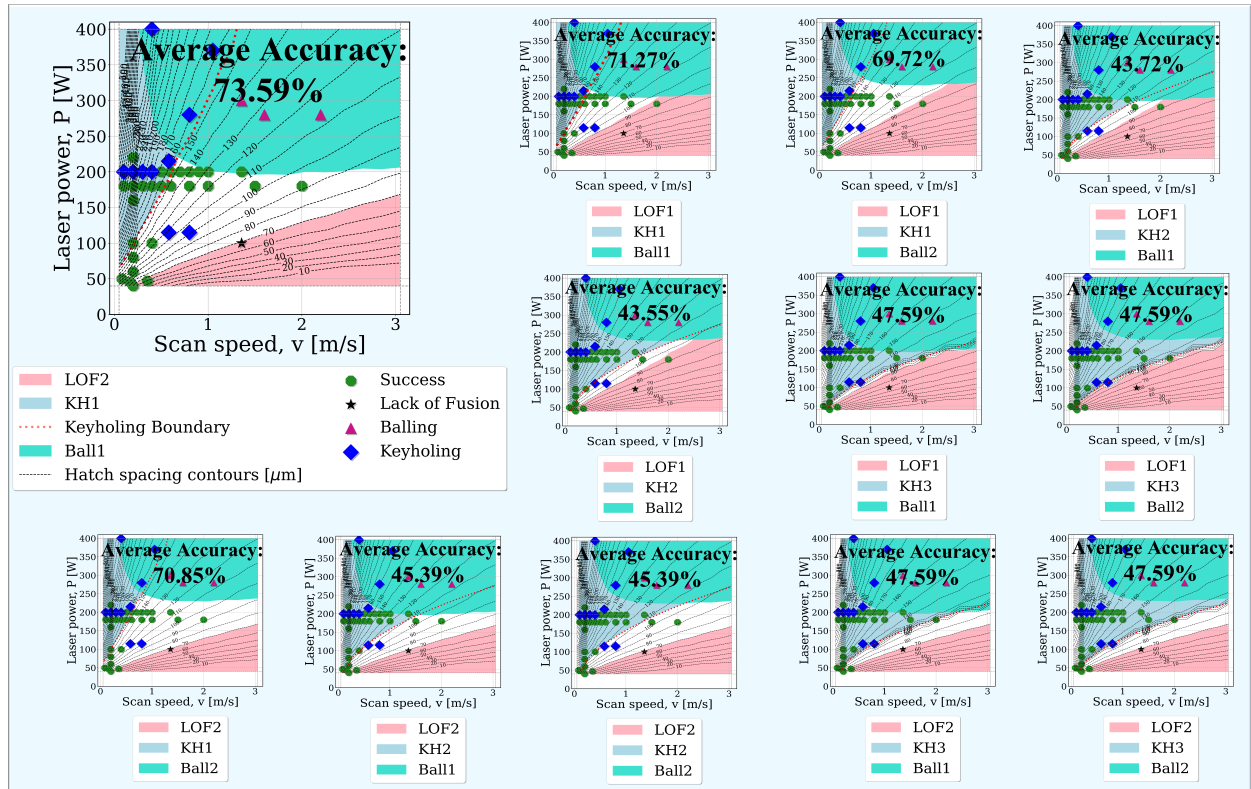
Supplementary Figure 1: Effect of Varying the Powder Layer Thickness and Hatch Spacing. By varying the powder layer thickness and hatch spacing for $\text{Ni}_{50.3}\text{Ti}_{49.7}$, different printability maps can be generated where the defect region (specifically for lack-of-fusion) changes. The hatch spacing varied from 75 μm to 90 μm while the powder layer thickness varied from 35 μm to 50 μm . By changing the hatch spacing and powder layer thickness, the defect region defined also changes to create a new printability map. LOF: Lack-of-fusion. KH: Keyholing. Ball: Balling. Salmon: Identifies the region where lack-of-fusion is predicted. Blue: Identifies the region where keyholing is predicted. Teal: Identifies the region where balling is predicted. Green circles: Experimentally observed defect-free single tracks. Black star: Experimentally observed lack-of-fusion. Magenta triangles: Experimentally observed balling. Blue diamond: Experimentally observed keyholing. Red dashed line: Keyholing boundary. Black dashed lines: Maximum hatch spacing required for sufficient overlap in a track in fully built parts.

Alloy Type	Single Track Datasets	Source	Beam Diameter [μm]	Powder Layer Thickness [μm]	L-PBF Machine
316 Stainless Steel	83	[20–23, 26, 27, 29]	52 [20], 55 [29], 70 [23, 27]	40 [21], 50 [20, 23], 75 [29], 80 [27]	DiMetal-100 [21], MCP Realizer SLM250 [22], Reinshaw AM400 [23]
Inconel 718	86	[30, 32–34, 36–38]	35[38], 60 [36], 70 [34], 100 [33]	30 [34], 40 [30, 37], 70 [33]	ReaLizer SLM 250 [38], BLT-S200 [36], EOS M290 [33]
Ti-6Al-4V	41	[39, 40, 42–44, 46]	70 [39, 43], 92 [42], 100 [44, 46]	20 [40], 30 [40, 43, 44, 46], 40 [40], 50 [42]	3D Systems ProX DMP 100 [39, 43], EOSINT M290 [44, 46], SLM-500 [37]
Ni-5Nb	49	Experimental data conducted at Texas A&M and published in [3, 45]	100 [3, 45]	30 [3, 45]	3D Systems ProX DMP 200 [3, 45]
AF96	64	Experimental data conducted at Texas A&M and published in [4]	80 [4]	37 [4]	3D Systems ProX DMP 200 [4]

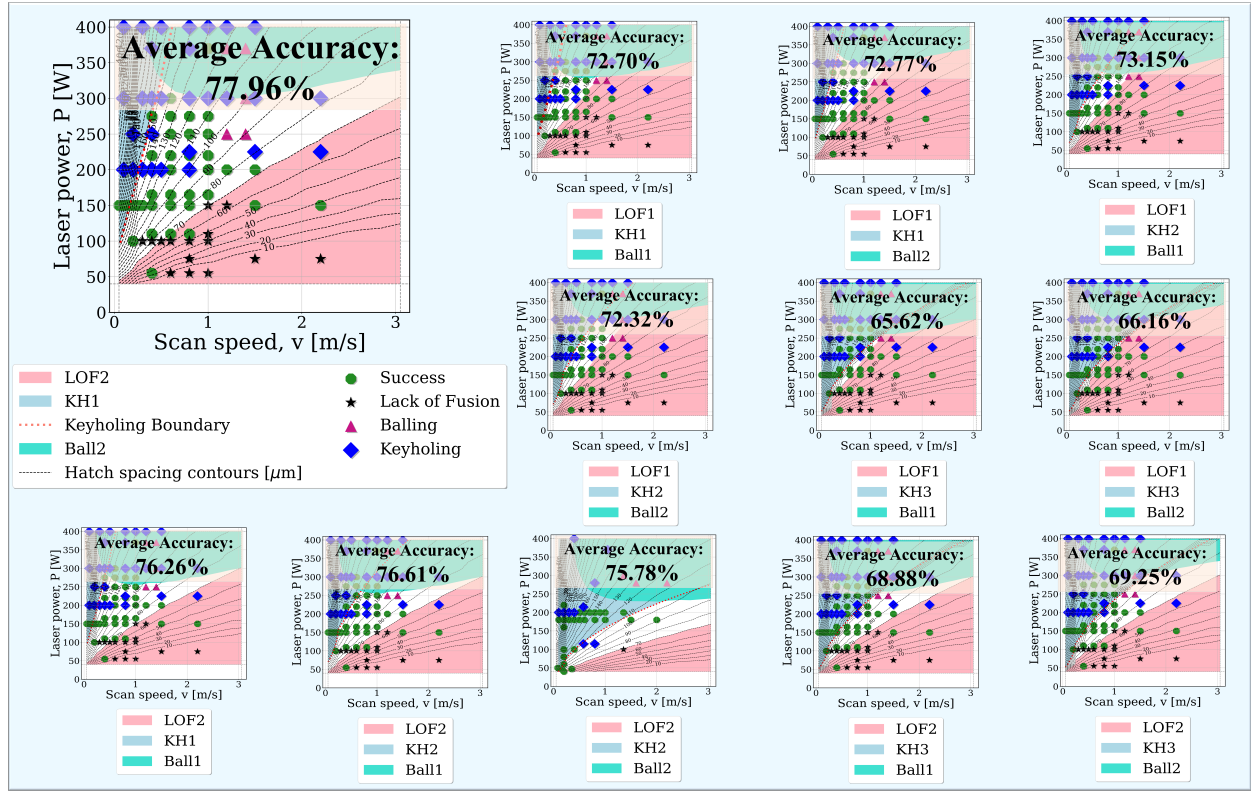
Supplementary Table 2: The table displays the number of experimental points used for each alloy to validate the printability maps. The sources, beam diameters, powder layer thicknesses, and L-PBF machines used for each dataset are specified to provide transparency on the experimental conditions for the points used to validate the framework. Some published data did not provide all information about their experimental setup. However, the criteria for data selection were based on whether the data points were for a single-track, whether power-velocity points were given, and whether any defect was stated.



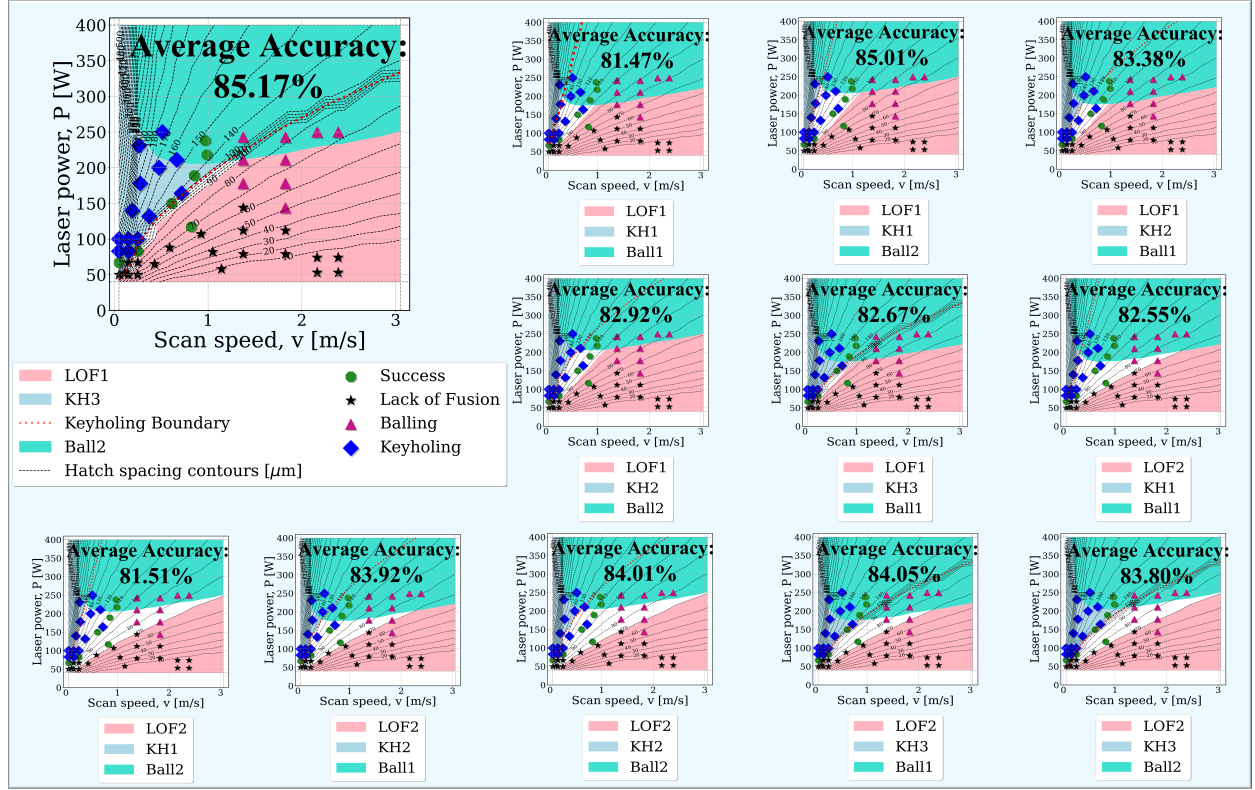
Supplementary Figure 2: Printability Maps for 316 Stainless Steel Using Combinations of Defect Criteria. Printability maps for 316 Stainless Steel were generated using various combinations of defect criteria for lack-of-fusion (LOF), balling (Ball), and keyholing (KH). The maps, presented in descending order of average accuracy, correspond to each criteria set. Overlaid experimental data facilitated the calculation of precision, recall, and accuracy for four binary classifications based on defect presence (i.e., lack-of-fusion, keyholing, balling, and success or defect-free). The corresponding values are also shown for each map. The highest average accuracy achieved was 83.96%. Defect labels (LOF, Ball, and KH) are detailed in Table 5. Salmon: Identifies the region where lack-of-fusion is predicted. Blue: Identifies the region where keyholing is predicted. Teal: Identifies the region where balling is predicted. Green circles: Experimentally observed defect-free single tracks. Black star: Experimentally observed lack-of-fusion. Magenta triangles: Experimentally observed balling. Blue diamond: Experimentally observed keyholing. Red dashed line: Keyholing boundary. Black dashed lines: Maximum hatch spacing required for sufficient overlap in a track in fully built parts.



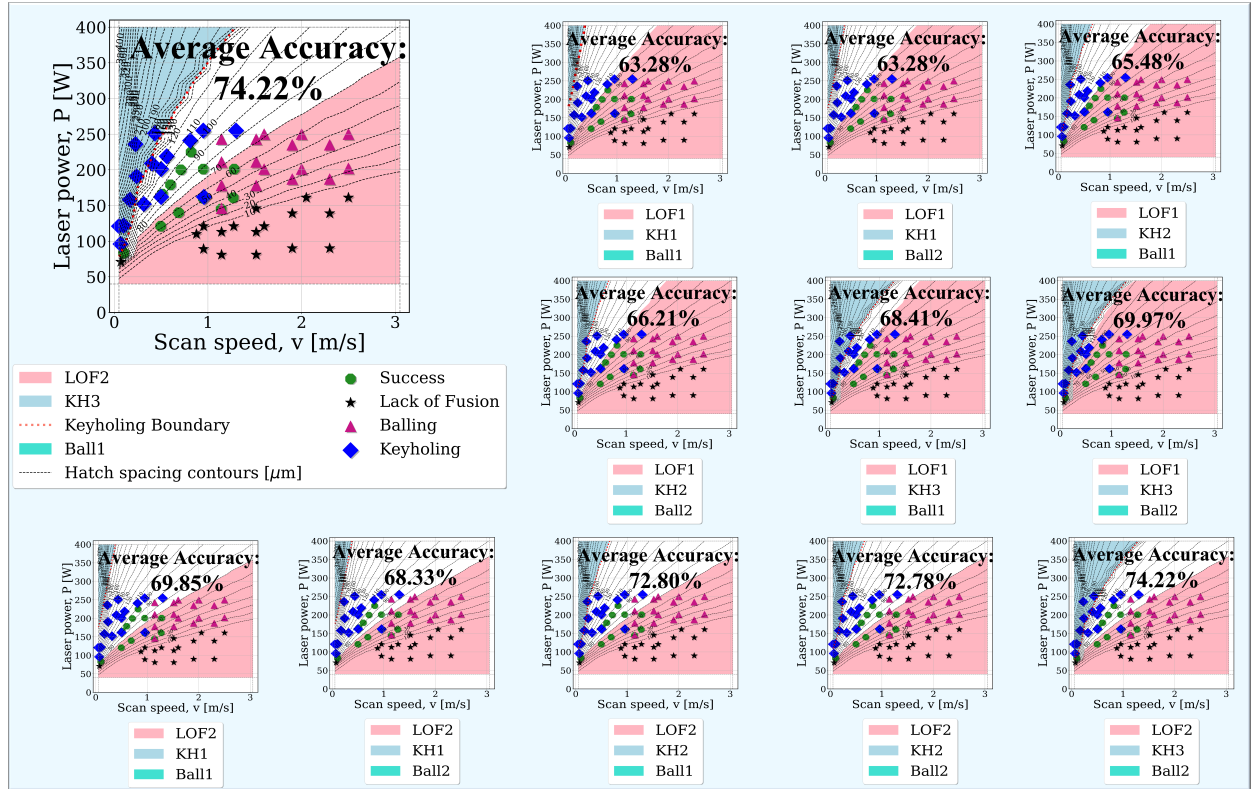
Supplementary Figure 3: Printability Maps for Ti-6Al-4V Using Combinations of Defect Criteria. Printability maps for Ti-6Al-4V were created using various defect criteria combinations for lack-of-fusion, balling, and keyholing. Precision, recall, and accuracy were calculated based on experimentally observed data and the package prediction for each case. The assessment was performed for four binary classification problems, defined by the presence or absence of each label (i.e., lack-of-fusion, keyholing, balling, and successful or defect-free prints). The highest average accuracy achieved was 73.59%. The definitions for defect labels (i.e., LOF, Ball, and KH) can be found in Table 5. Salmon: Identifies the region where lack-of-fusion is predicted. Blue: Identifies the region where keyholing is predicted. Teal: Identifies the region where balling is predicted. Green circles: Experimentally observed defect-free single tracks. Black star: Experimentally observed lack-of-fusion. Magenta triangles: Experimentally observed balling. Blue diamond: Experimentally observed keyholing. Red dashed line: Keyholing boundary. Black dashed lines: Maximum hatch spacing required for sufficient overlap in a track in fully built parts.



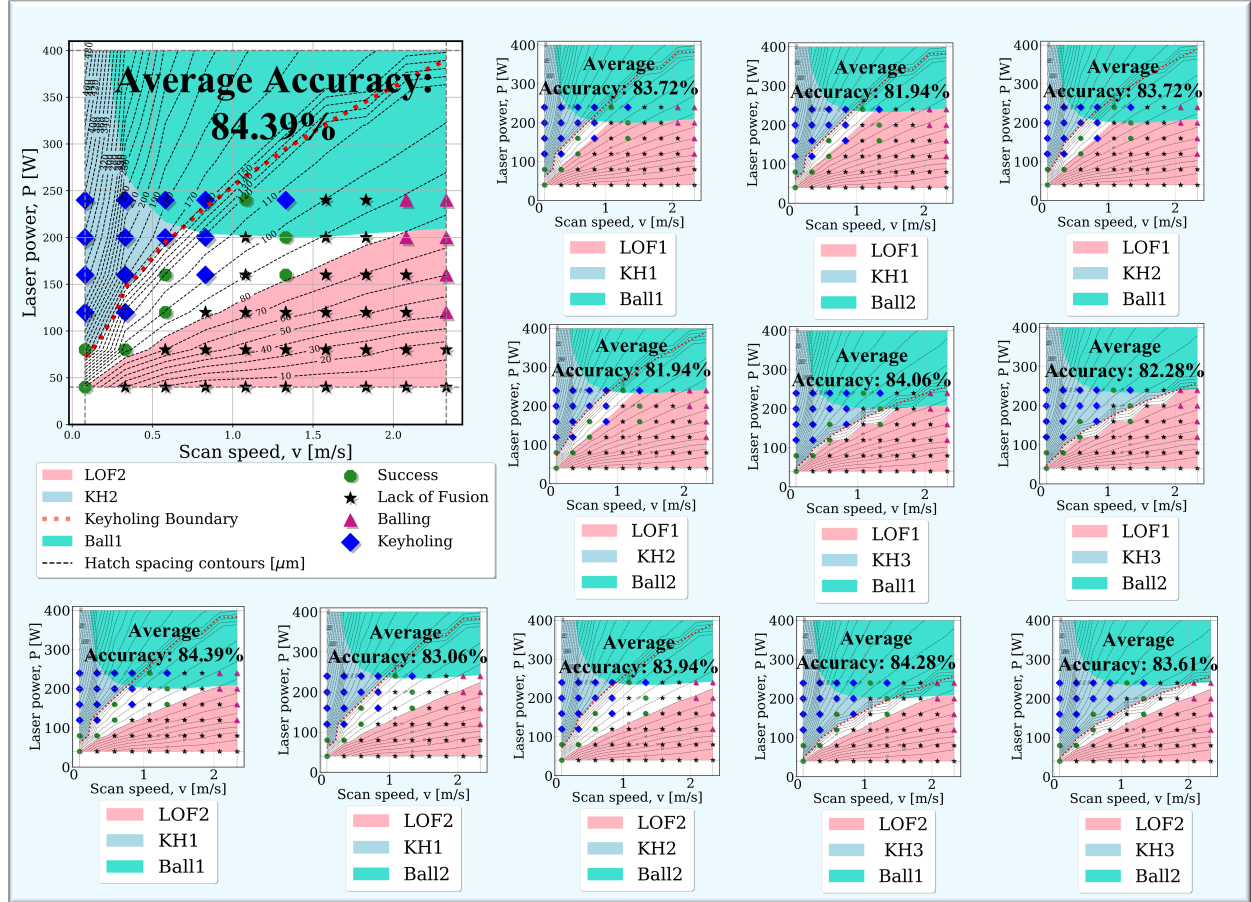
Supplementary Figure 4: Printability Maps for Inconel 718 Using Combinations of Defect Criteria. The printability maps were produced using different combinations of defect criteria for lack-of-fusion, balling, and keyholing for Inconel 718. Based on the experimentally observed data and the package prediction in each case, the precision, recall, and accuracy were calculated for four binary classification problems defined based on the presence and absence of each label (i.e., lack-of-fusion, keyholing, balling, and success or defect-free) in the printability maps and then their averages were listed. Each map corresponds to a different criteria combination. The maximum value for average accuracy was 77.96%. The definitions for defect labels (i.e., LOF, Ball, and KH) can be found in Table 5. Salmon: Identifies the region where lack-of-fusion is predicted. Blue: Identifies the region where keyholing is predicted. Teal: Identifies the region where balling is predicted. Green circles: Experimentally observed defect-free single tracks. Black star: Experimentally observed lack-of-fusion. Magenta triangles: Experimentally observed balling. Blue diamond: Experimentally observed keyholing. Red dashed line: Keyholing boundary. Black dashed lines: Maximum hatch spacing required for sufficient overlap in a track in fully built parts.



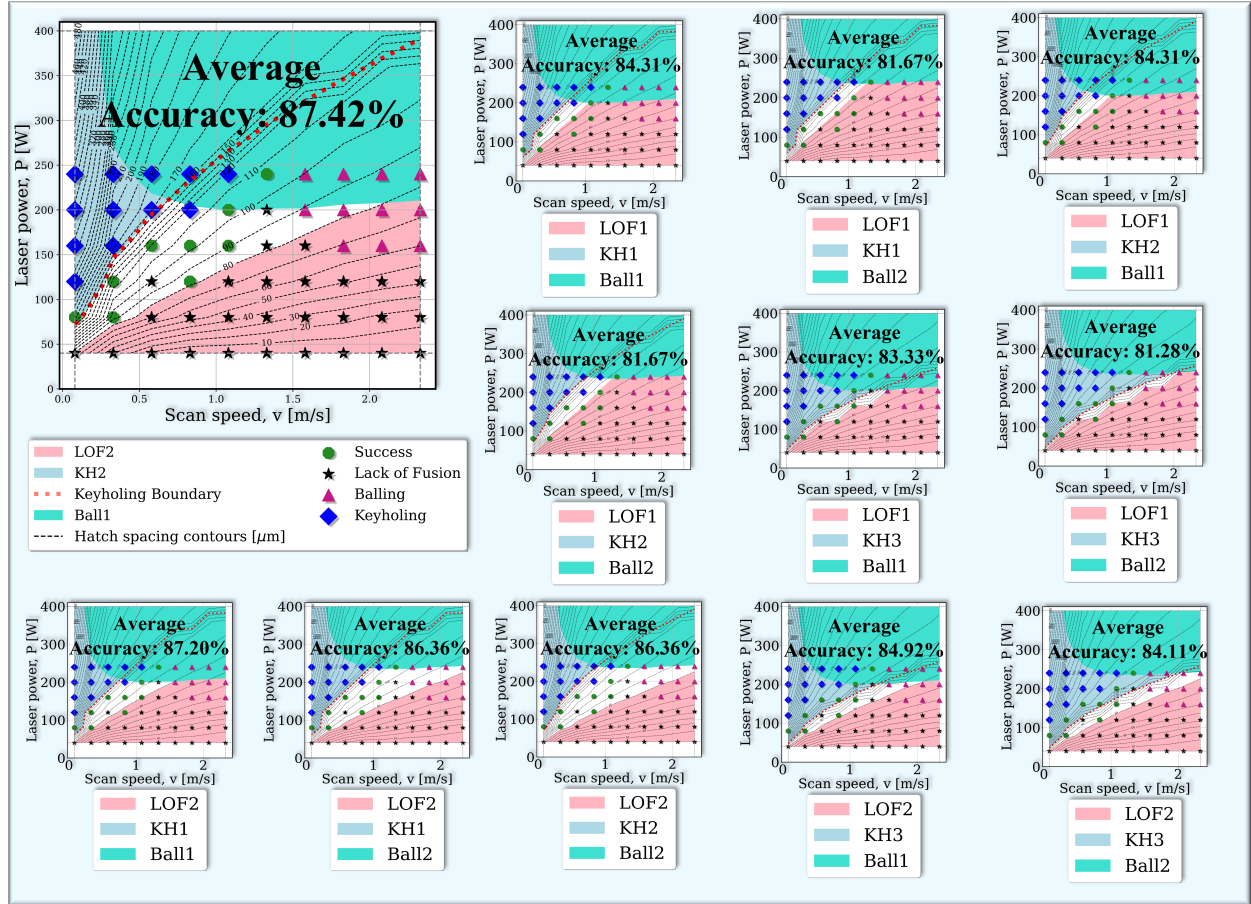
Supplementary Figure 5: Printability Maps for AF96 Using Combinations of Defect Criteria. Printability maps for AF96 have been derived from various defect criteria combinations for lack of fusion (LOF), balling (Ball), and keyholing (KH), where each map represents a different criteria combination. The precision, recall, and accuracy values are calculated from four binary classification problems established on the presence or absence of each defect label in the printability maps, and the average accuracy is displayed. The highest observed average accuracy is 85.17%. The definitions for the defect labels are provided in Table 5. Salmon: Identifies the region where lack-of-fusion is predicted. Blue: Identifies the region where keyholing is predicted. Teal: Identifies the region where balling is predicted. Green circles: Experimentally observed defect-free single tracks. Black star: Experimentally observed lack-of-fusion. Magenta triangles: Experimentally observed balling. Blue diamond: Experimentally observed keyholing. Red dashed line: Keyholing boundary. Black dashed lines: Maximum hatch spacing required for sufficient overlap in a track in fully built parts.



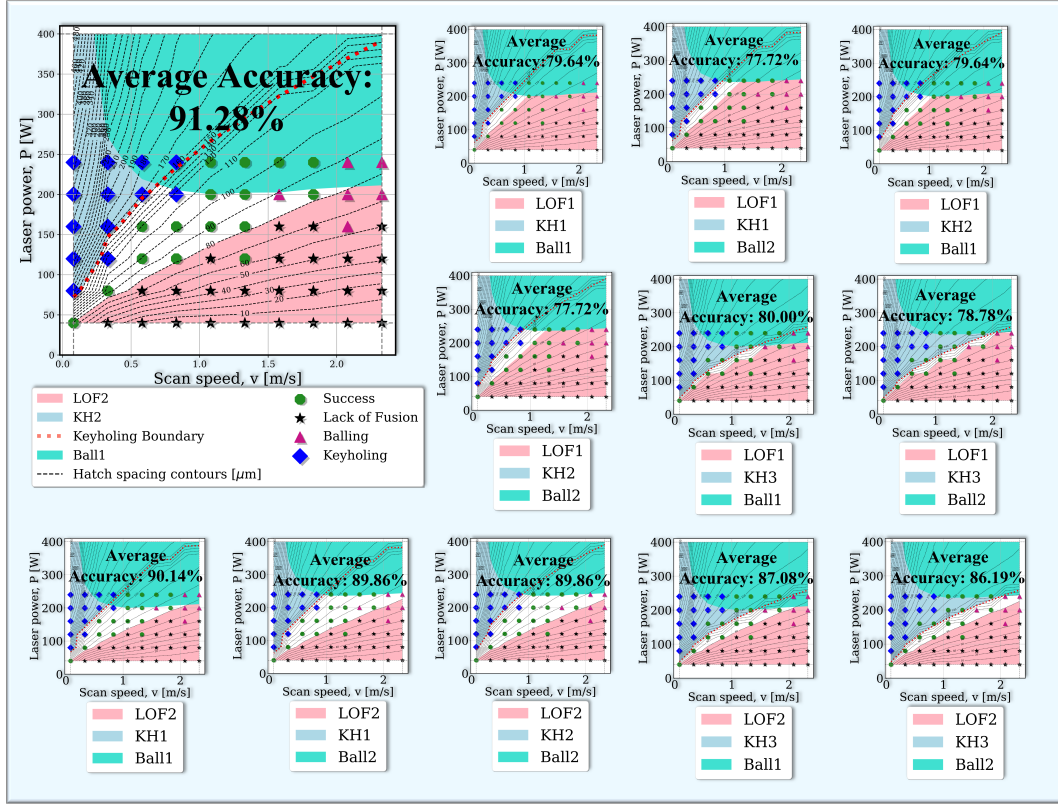
Supplementary Figure 6: Printability Maps for Ni-5Nb Using Combinations of Defect Criteria. Printability maps for Ni-5Nb (weight 5%), illustrating various defect criteria combinations for lack-of-fusion (LOF), balling (Ball), and keyholing (KH). Each map corresponds to a distinct criteria combination, arranged in decreasing order of average accuracy. Precision, recall, and accuracy values are calculated from four binary classification problems based on the presence or absence of each defect label. The highest average accuracy observed is 74.22%. The definitions for the defect labels are provided in Table 5. Salmon: Identifies the region where lack-of-fusion is predicted. Blue: Identifies the region where keyholing is predicted. Teal: Identifies the region where balling is predicted. Green circles: Experimentally observed defect-free single tracks. Black star: Experimentally observed lack-of-fusion. Magenta triangles: Experimentally observed balling. Blue diamond: Experimentally observed keyholing. Red dashed line: Keyholing boundary. Black dashed lines: Maximum hatch spacing required for sufficient overlap in a track in fully built parts.



Supplementary Figure 7: Printability Maps for $\text{Ni}_{50.3}\text{Ti}_{49.7}$ Using Combinations of Defect Criteria. The printability maps were produced using different combinations of defect criteria for lack-of-fusion, balling, and keyholing for $\text{Ni}_{50.3}\text{Ti}_{49.7}$. Based on the experimentally observed data and the prediction in each case, the precision, recall, and accuracy were calculated for four binary classification problems defined based on the presence and absence of each label (i.e., lack-of-fusion, keyholing, balling, and success or defect-free) in the printability maps. The average accuracy for each map is listed. Each map corresponds to a different criteria combination. The maximum value for average accuracy was 84.39%. The definitions for the defect labels are provided in Table 5. Salmon: Identifies the region where lack-of-fusion is predicted. Blue: Identifies the region where keyholing is predicted. Teal: Identifies the region where balling is predicted. Green circles: Experimentally observed defect-free single tracks. Black star: Experimentally observed lack-of-fusion. Magenta triangles: Experimentally observed balling. Blue diamond: Experimentally observed keyholing. Red dashed line: Keyholing boundary. Black dashed lines: Maximum hatch spacing required for sufficient overlap in a track in fully built parts.



Supplementary Figure 8: Printability Maps for $\text{Ni}_{50.8}\text{Ti}_{49.2}$ Using Combinations of Defect Criteria. The printability maps were produced using different combinations of defect criteria for lack-of-fusion, balling, and keyholing for $\text{Ni}_{50.8}\text{Ti}_{49.2}$. Based on the experimentally observed data and the package prediction in each case, the precision, recall, and accuracy were calculated for four binary classification problems defined based on the presence and absence of each label (i.e., lack-of-fusion, keyholing, balling, and success or defect-free) in the printability maps and the average accuracy was listed. Each map corresponds to the different criteria combination. The maximum value for average accuracy was 87.42%. The definitions for the defect labels are provided in Table 5. Salmon: Identifies the region where lack-of-fusion is predicted. Blue: Identifies the region where keyholing is predicted. Teal: Identifies the region where balling is predicted. Green circles: Experimentally observed defect-free single tracks. Black star: Experimentally observed lack-of-fusion. Magenta triangles: Experimentally observed balling. Blue diamond: Experimentally observed keyholing. Red dashed line: Keyholing boundary. Black dashed lines: Maximum hatch spacing required for sufficient overlap in a track in fully built parts.



Supplementary Figure 9: Printability Maps for $\text{Ni}_{51.2}\text{Ti}_{48.8}$ Using Combinations of Defect Criteria. The printability maps were produced using different combinations of defect criteria for lack-of-fusion, balling, and keyholing for $\text{Ni}_{51.2}\text{Ti}_{48.8}$. Based on the experimentally observed data and the package prediction in each case, the precision, recall, and accuracy were calculated for four binary classification problems defined based on the presence and absence of each label (i.e., lack-of-fusion, keyholing, balling, and success or defect-free) in the printability maps and then their averages were listed. Each map corresponds to a different criteria combination. The maximum value for average accuracy was 91.28%. The definitions for the defect labels are provided in Table 5. Salmon: Identifies the region where lack-of-fusion is predicted. Blue: Identifies the region where keyholing is predicted. Teal: Identifies the region where balling is predicted. Green circles: Experimentally observed defect-free single tracks. Black star: Experimentally observed lack-of-fusion. Magenta triangles: Experimentally observed balling. Blue diamond: Experimentally observed keyholing. Red dashed line: Keyholing boundary. Black dashed lines: Maximum hatch spacing required for sufficient overlap in a track in fully built parts.

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