Machine-learning assisted prediction of surface roughness in powder bed fusion process with Inconel super alloy

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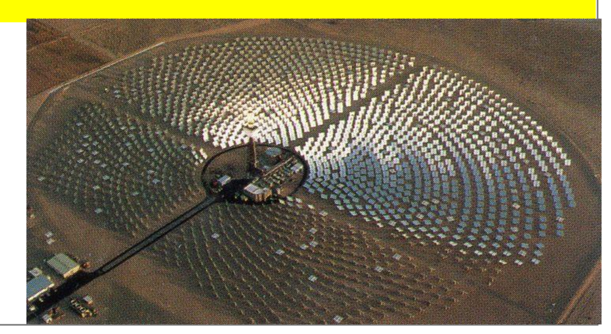
Problem Statement

- Selective Laser Melting (SLM) is an Additive Manufacturing (AM) is a method additively combines layers until a full part requires minimal post-processing. The main goal of this project is to train a machine learning algorithm to predict the vertical wall line surface area roughness of a print given a power and hatch distance input for Inconel 718.

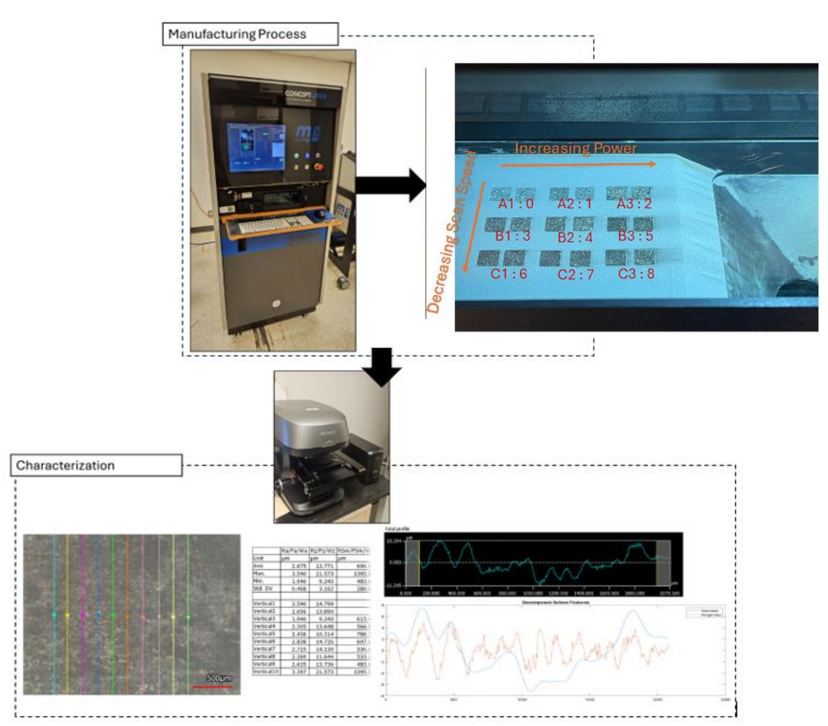
Brief Literature Review

- Concentrated Solar Power (CSP) is a growing technology that utilizes directly utilizes solar energy. A limitation of this system is the absorptivity of the Receivers, this is usually bypassed using paints like Pyromark 2500 but the lifetime for this material is low and causes significant downtime.



Experimental Setup and Collection of Data

- 1 initial set of coupons was printed, and 2 additional replica sets were produced to generate a reasonable set of training data using the GM Concept laser. There was 9 different printing parameters and for this situation each is considered its own label.
- The sample coupons were removed from the substrate and .csv files were extracted from line profiles using the Keyence VK-X3000. The profiles were used directly for training the machine learning algorithm

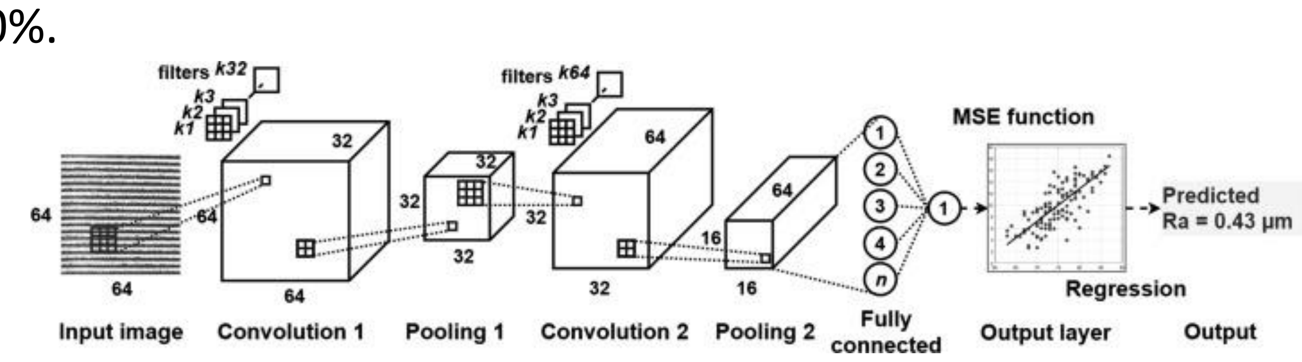


		Power (W)			
		100	**150**	**190**	**VED (J/mm3)**
Scan Speed (mm/s)	**800**	34.7	52.1	66.0	
	600	46.3	69.4	88.0	
	400	69.4	104.2	131.9	

- The data is labeled according to a grid, A ,B, and C reference the scanning speed of the laser while the subsequent numbers 1, 2, 3, refer to the Laser power.

Method(s)

- Multiple methods were utilized to attempt a high-accuracy classification of the surface roughness, considering that the data can vary highly between each data set it was imperative that the machine learning algorithm be largely generalized.
- FFT, STFT, MFCC, and DWT were all attempted but could not yield a validation or test accuracy of above 40 % for a simple forward feed Neural Network and SVM
- Utilizing CNN utilizing the raw 2D line profile Data proved the most effective easily reaching an accuracy of 60%.

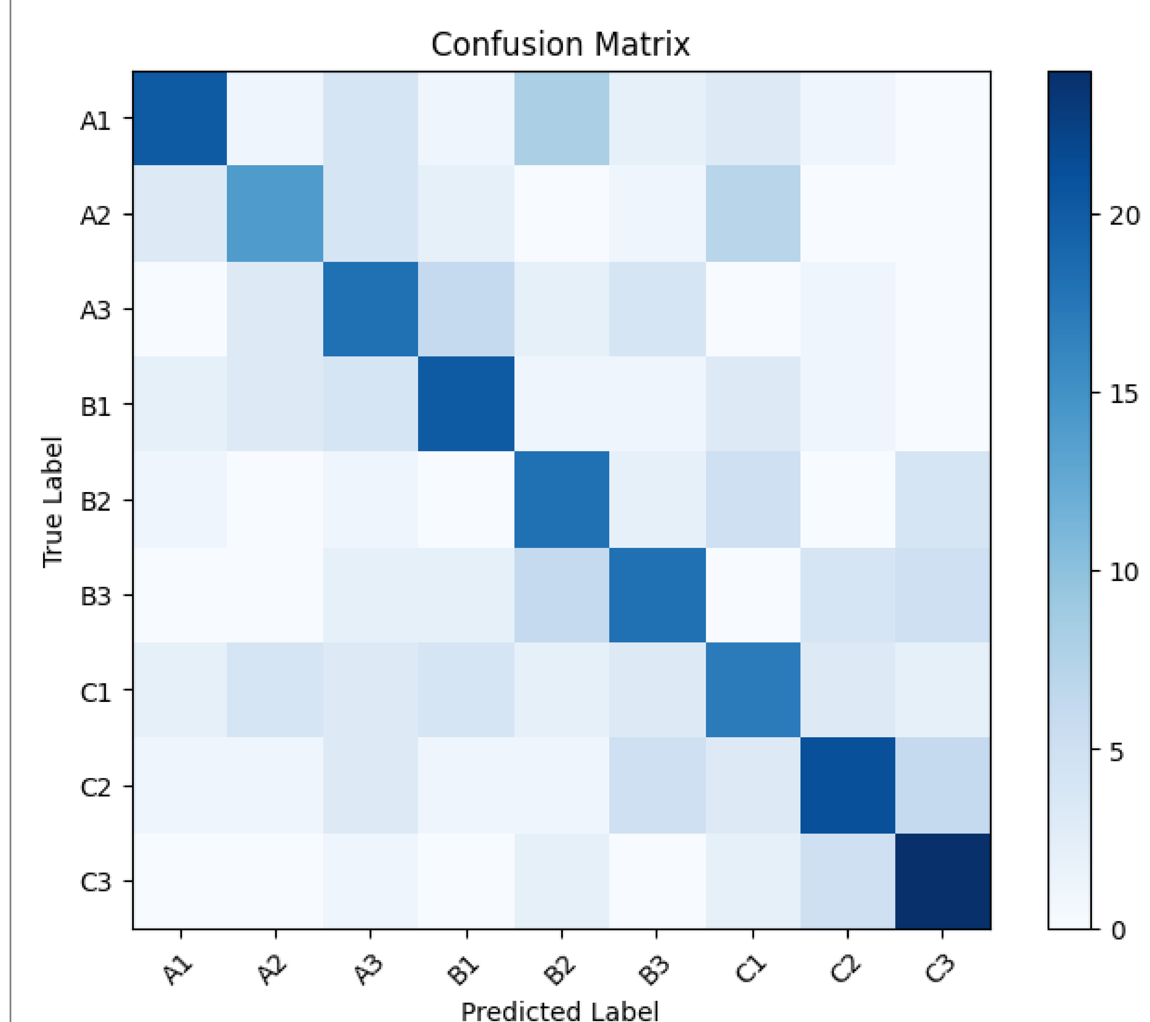


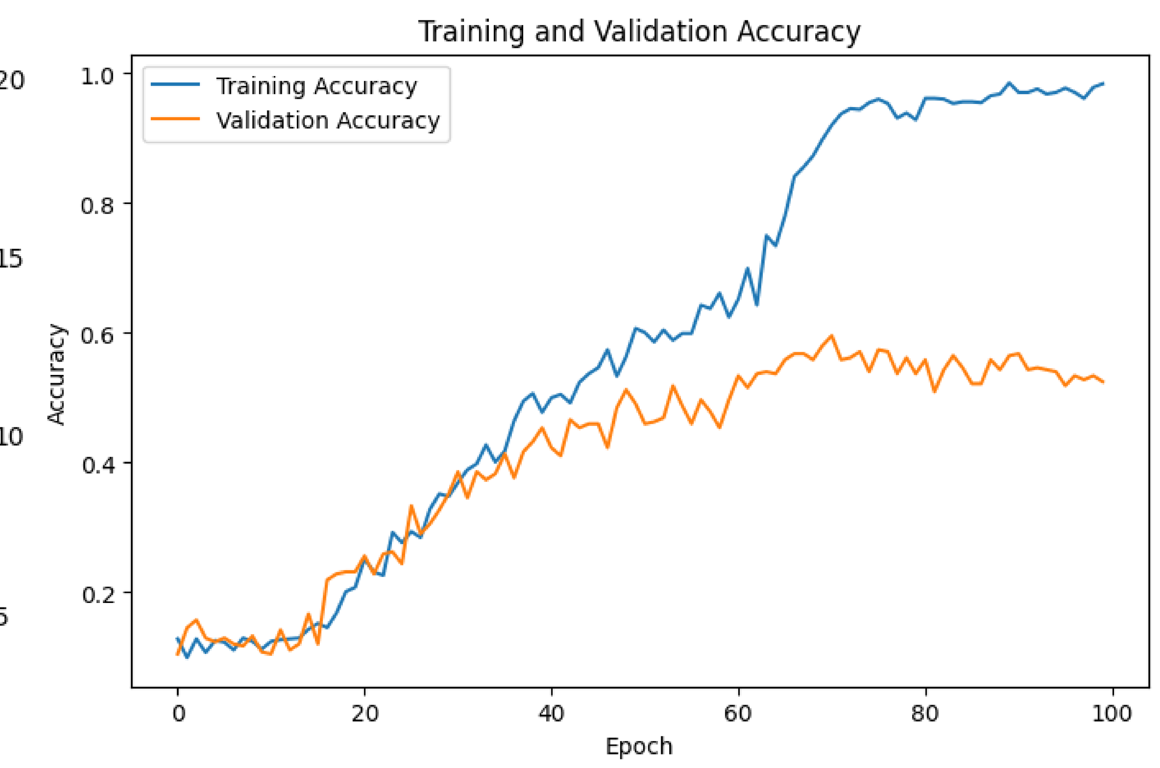
Rifai, A. P., Aoyama, H., Tho, N. H., Dawal, S. Z. M., & Masruroh, N. A. (2020). Evaluation of turned and milled surfaces roughness using convolutional neural network. *Measurement*, *161*, 107860.

- The main Highlight of this work is considering that Ra value may not be truly representative of the surface roughness of a sample in SLM and such we attempt to classify the roughness more rigorously; for an early attempt the printing parameters were used as labels.

Results, Analysis and Discussion

- CNN worked as the most reliable and repeatable option for classification. While this method didn't exceed 60%s similar models from other studies were able to achieve 80% at minimum.
- While a clear trend was present there is still clearly overfitting at this moment.
- The model is expected to change largely to suggest printing parameters for this material.





- As mentioned in the previous section, most data extraction methods did not result in good machine learning training
- Comparatively CNN worked well to achieve classification
- STFT and MFCC are technically auditory feature extraction techniques and thus work well with repeatable auditory data but not necessarily with nonrepeatable surface profiles
- The Project has definite prospects in the future despite the current difficulties.

Conclusion

- While not entirely fruitful the signal extraction method of FFT, STFT, MFCC, and DWT were all used to try to classify surface profiles to their printing parameters. This is an ongoing effort that is planned for future development.
- This work stands out from previous research as previous works tend to classify only Ra value; this is not indicative of true surface roughness while some studies try to use multiple values such as Rz etc. it does not provide clear data about surface profile since it is averaged data.
- Future work is intended to have the algorithm suggest printing parameters for a given desired surface roughness, with more time it is desired that image-based data (topography data) be used to drive printing parameter selection

Acknowledgements

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References

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