Quality Engineering for 3D Printing

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Introduction

- Laser-Based Additive Manufacturing (LBAM), commonly known as metal 3D printing, is the process of melting metal pellets to manufacture products with minimal waste compared to traditional manufacturing.
- During the printing process, air bubbles may get trapped in the metal melt pool which introduces porosity in the final product.
- Creating a Neural Network (NN) to detect such porosities to manufacture parts that do not prematurely fail and cause additional problems to the users and manufacturers.
- By increasing the complexity of the NN through increasing layer count, reducing input size, and using mean squared error as the cost function, we achieved a 93.33% accuracy on unseen test cases.

Background

(Khanzadeh et al, 438)

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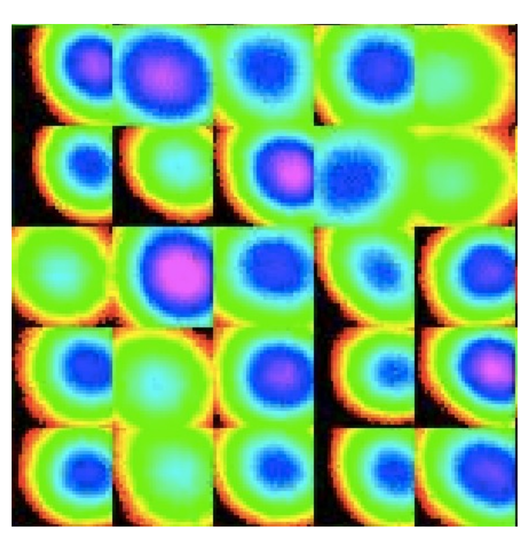
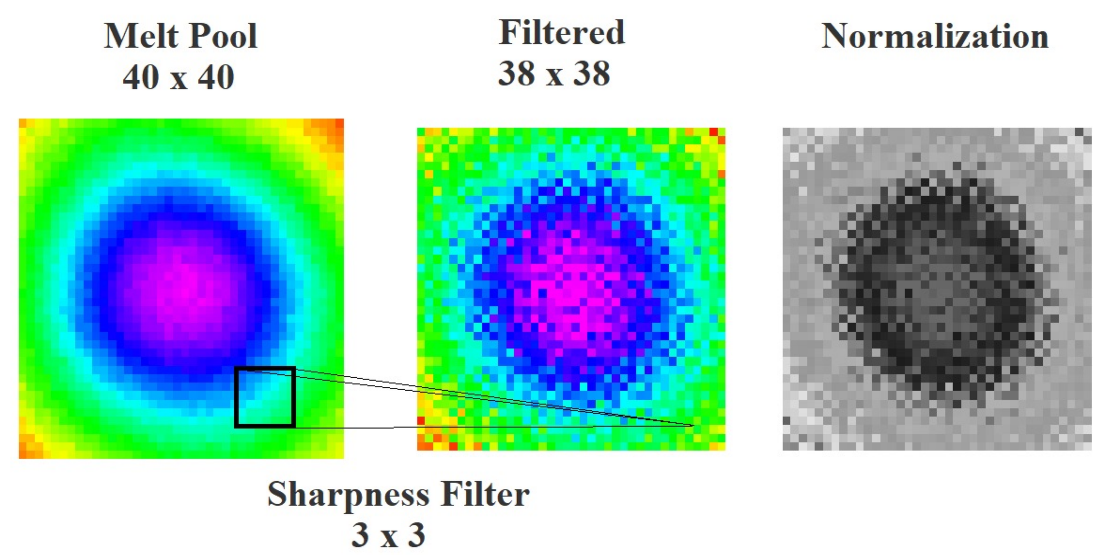
These are known as porosity: air bubbles and residues that get trapped within the melt pool that are impossible to remove after printing. **They weaken the internal structure of the printed product, causing premature failure for the end user to experience.** And the only way to check for these errors are by using x-ray and ultrasonic machines which limits the scan size and is quite expensive to operate.

In order to detect and eliminate these porosities, we decided to use a Neural Network (NN) to actively check if the current melt pool could produce a porosity. Originally, the data comes from a heatmap of the entire heat bed of the 3D printer (752 x 480). The input of the NN is altered to be a 40 x 40 matrix with the hottest point of the melt pool in the center in that matrix. Previous studies based on porosity management have analyzed the shape of the melt pool in polar coordinate terms.

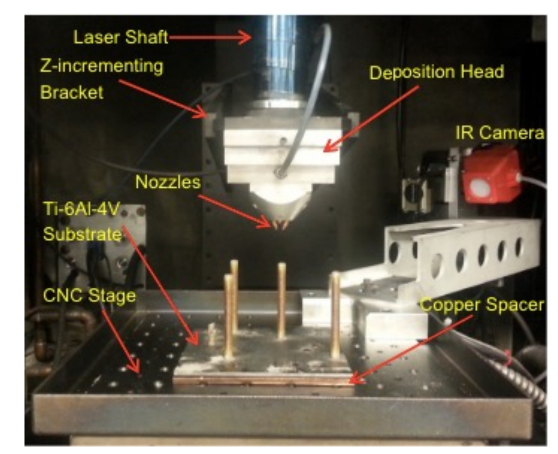


This is a collection of 25 melt pools that are visually represented by a gradient from 1500 to 2100 Celsius. These melt pools are going to be input to the NN as a flattened array.

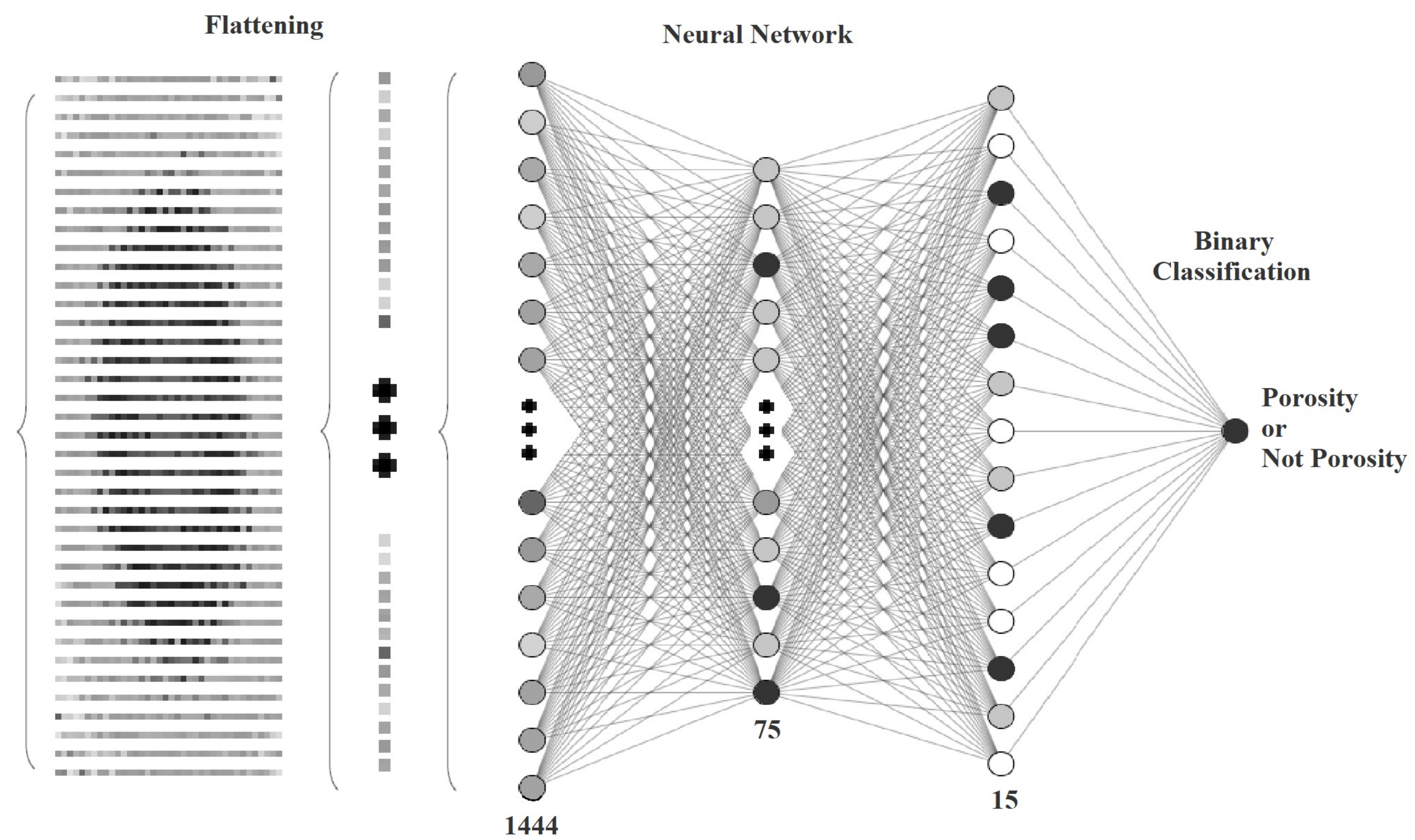
Neural Network



This is the 3D printer set up: there are two different sensors that are surrounding the heat bed to capture the melt pool characteristics. The recorded data from these sensors were labeled with time and location of the hot end, allowing the mapping of porosity possible after printing.

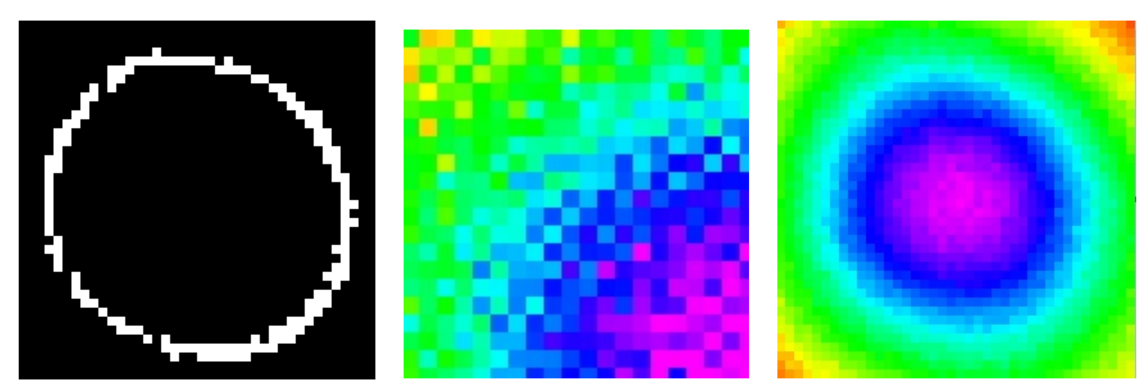


(Marshall et. al, 700)



This is the neural network that achieved the highest accuracy out of the different NN we have tested. It first conducts a sharpness filter throughout the matrix to emphasize the feature. Then, it performs a flattening and a normalizing function in order to regulate the input. The flattened array then becomes the input of the NN which was 2 hidden layers of size 75 and 15 nodes, respectively. It performs a sigmoid function for the activation function. Then, it is binary classified: yes or no porosity. For this specific model, a simple mean squared error was used as the error function during backpropagation and achieved a 93.33% accuracy on unseen test cases.

Procedure



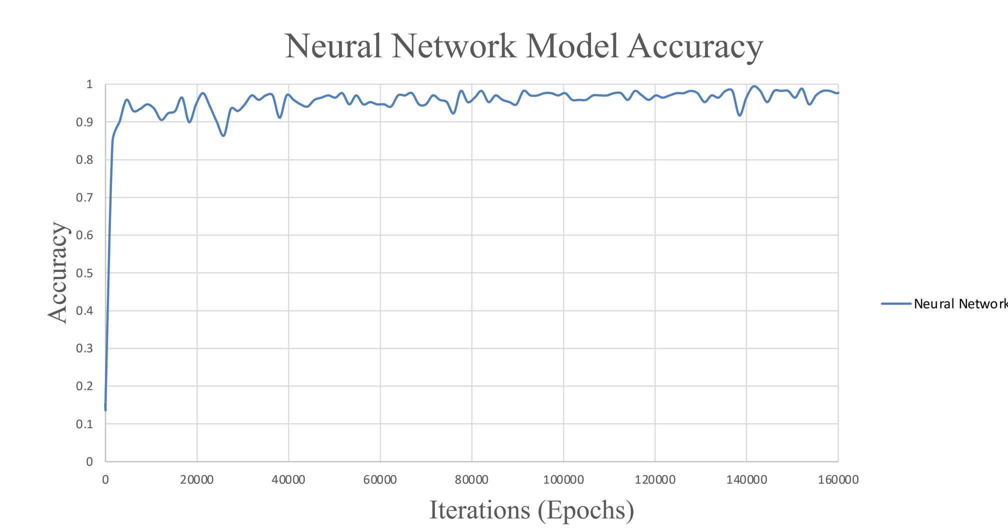
Throughout the research, there were many discussion about which data to use for the input for the NN: **40 x 40, 30 x 30, quarter set, outline set, and adaptive sampling**. In most cases, the 40 x 40 data was utilized as it captured most the melt pool shape and property of the set.

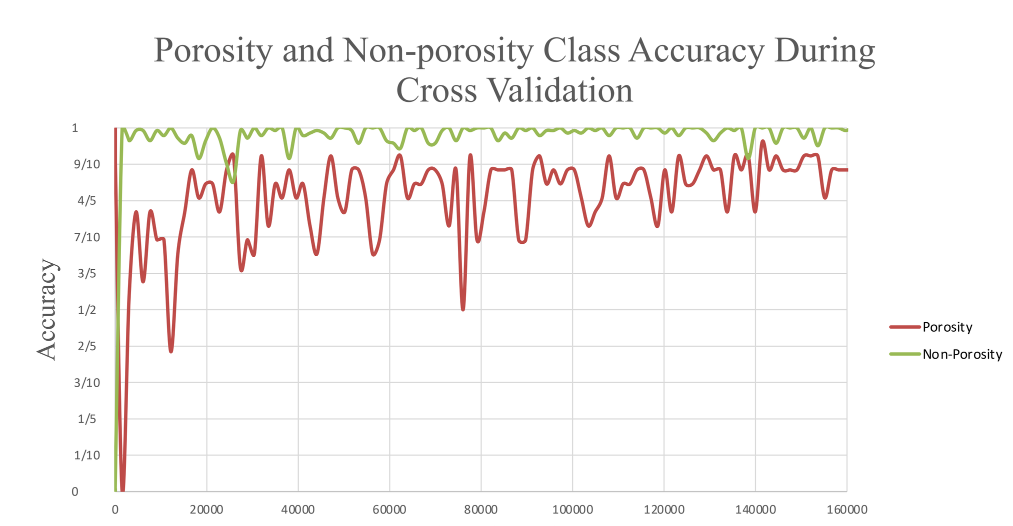
$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2 \qquad F_\beta = \frac{(1+\beta^2)\mathrm{tp}}{(1+\beta^2)\mathrm{tp} + \beta^2\mathrm{fn} + \mathrm{fp}}$$

For the backpropagation error function, we primary used 2 cost functions: mean squared and F-measure to account for an imbalanced data set. Ideally, there would be an equal amount of data sets for the 2 classes: porosity and non-porosity. However, there were around 1,500 sets for non-porosity and only 71 sets for porosity cases, 284 after rotated cases. By adopting some edge cases when there was a limited amount of porosity cases, we could emphasize the change in beta weights when there were more porosity cases to alter the NN weight even more.

During the research, many combinations of inputs and error functions were tested to determine which configuration worked the best for the NN accuracy. There were also other features that were implemented on some configurations such as logarithmic delta for change in weights and bias nodes. There were some minor challenges when implementing the F-measure: this was solved however using a batches for iterations rather than the samples themselves directly.

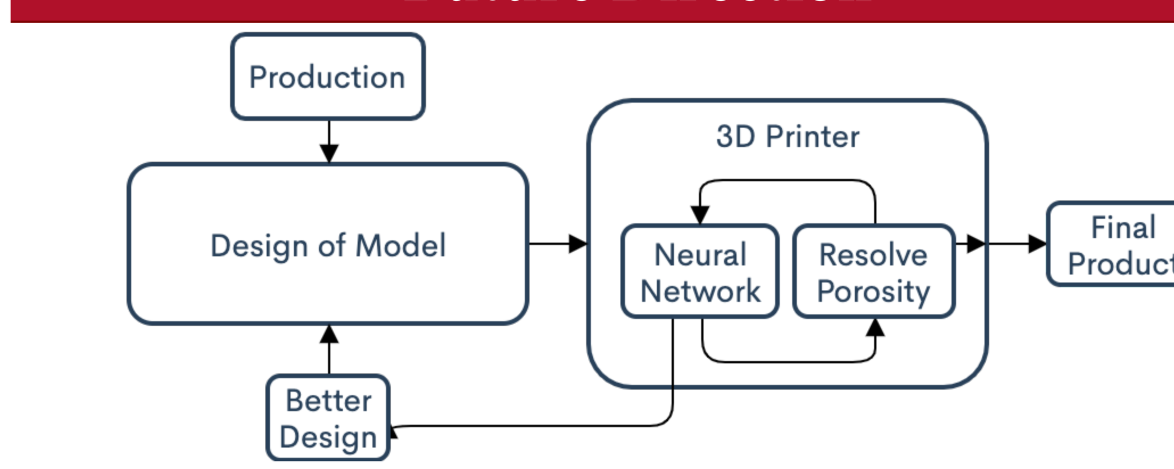
Results





Due to the sheer inequality in the number of cases between the porosity and non-porosity classes, the NN was able to learn the non-porosity cases relatively easily. In most cases, the NN could learn this class just under 5000 iterations (3 epochs). **On the other hand, the NN managed to achieve around 93.33% accuracy rate around the 140,000 iterations.** All were tested and recorded with ten-fold cross validation. Most combinations achieved an accuracy better than an 88% apart from the outline inputs and quarter as inputs. However, sharpness filtering accompanies by a normal NN gave us the best results in accuracy.

Future Direction



From this research, it would be ideal to implement the NN on a live metal 3D printer to observe if it can actively fix the porosities. Currently, the system only records the heat map of the heat bed in a .csv file with the respective time and location of the hot end. **Creating this NN is just a small portion in developing a better manufacturing process for all users to benefit.** It would be possible to use the on-board computer to alter the current printing characteristics to reduce the porosity.

Open Source on GitHub

For this project, I made it publicly available so that other researchers and developers can utilize the NN weights instead and enable them to research deeper into metal 3D printing. There is also a simple version of the NN that does the calculation for you if you just input your temperature file directory.

Acknowledgements

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References

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