Machine Learning for Printed Electronics

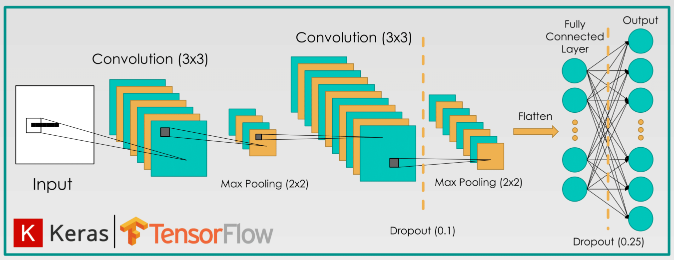
BACKGROUND

The aim of this project is to develop a machine learning algorithm to optimize pattern fidelity in printed electronics. Printed electronics enables the production of highly customizable, low-cost microelectronic devices. One of the challenges with them however, is that once printed, ink can flow and cause errors such as bulging in the desired shape. Our group has done prior work to print simple shapes with minimal distortions by changing the ordering of drops. Using these findings, we are developing a convolutional neural network (CNN) that will take an image of an arbitrary circuit pattern as the input for which an optimal printing sequence is not known and produce that sequence.

One of the non-idealities that can form when printing lines using a simple sequential order is bulging.

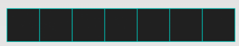
MODEL

To construct the CNN, the Keras open source library was used, which runs on top of the TensorFlow machine learning software library.



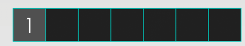
Several different structures with varying parameters were experimented with. One model that produced results with a high degree of accuracy is seen above. It was trained on 33,768 line images and then tested on 11,880 images that were not in the training set.

Tens of thousands of line images were generated with varying lengths and representing different drops within the printing process. Each image has a size of 61x61 pixels and is an input to the CNN. The output is one of 3722 possible pixels, representing a drop location.



1. Initially, a solid black line is given as an input.

2. The CNN predicts the location of the first drop.

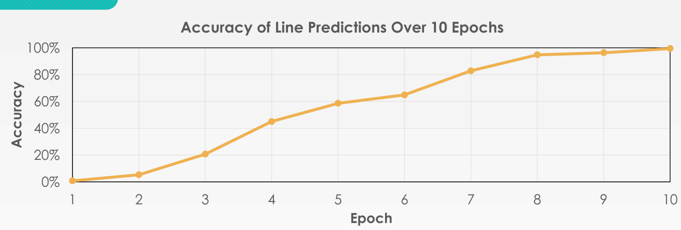


3. The algorithm reduces the RGB value of the pixel.

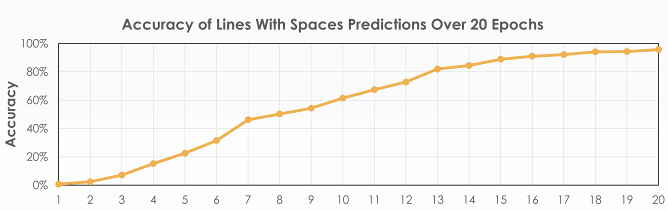
The new image is then passed back into the CNN to obtain the prediction for the next drop location, which will have a lower RGB value than the previous drop. This process is repeated until the final image contains the complete drop sequence.

RESULTS

The model requires several training cycles to sufficiently learn from the training images and accurately predict the next drop location.

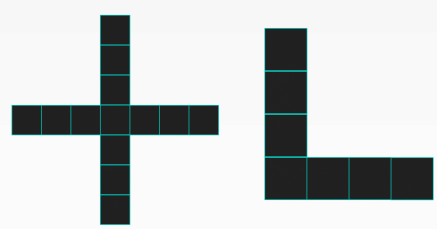


Spaces in between the pixels were introduced to represent the variable spacing in between each drop from the printer. The CNN was modified to handle these extra features.



CONCLUSION

The successful results with these lines has given us a platform to start from. The CNN has been modified to handle X-shapes, L-shapes, and other designs.



Work now continues to allow the CNN to handle even more complex design patterns and contribute to this unexplored area within printed electronics.

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