Artificial intelligence and machine learning to guide printed electronics fabrication

A Design Project Report

Presented to the School of Electrical and Computer Engineering of Cornell University

in Partial Fulfillment of the Requirements for the Degree of

Master of Engineering, Electrical and Computer Engineering

Submitted by:
Syed Askari Raza
Aditi Rao
Haochen Luo
Hardik Hedaoo

MEng Field Advisor: Professor Peter Doerschuk
MEng Outside Advisor: Ben Davaji

Degree Date: May 2024

Abstract

Master of Engineering Program
School of Electrical and Computer Engineering

Cornell University
Design Project Report

Project Title: Artificial intelligence and machine learning to guide printed electronics fabrication

Author: Syed Askari Raza , Aditi Rao ,Haochen Luo , Hardik Hedaoo

Abstract:

This project, led by Prof. Peter Doerschuk at Cornell University, in collaboration with Northeastern University, Bot Factory, and Geegah LLC, focuses on optimizing Flexible Hybrid Electronics (FHE) printing using advanced AI models and ultrasound metrology. The primary goal is to enhance print outcomes, such as predictability and control of printed line widths and thicknesses, by leveraging GHz ultrasonic imaging and AI technologies. The team aims to develop new software modules for image processing and AI/ML models, integrating innovations from industry partners to address the challenges of low yield in printed electronics boards. The project, with a duration of 18 months and a total cost of $898K, involves a comprehensive approach, including designing experiments, constructing databases, and training AI/ML models for image and vector transformations. The initiative also includes the development of new methodologies for measuring critical dimensions in printed electronics and optimizing printing parameters for improved outcomes. This interdisciplinary effort combines expertise in microsystem engineering, ultrasonics, biomedical sensors, and CMOS - MEMS to advance the field of FHE manufacturing.

Executive Summary

Accomplishments : Our team successfully integrated advanced technologies to create an approach for designing and validating electronic components. By combining 2D electronics printing with generative adversarial networks (GANs) and machine learning (ML), we developed an algorithm for predicting, assessing, and optimizing the characteristics of printed circuit boards (PCBs).

A key innovation in our approach is the development of a Generative Adversarial Network (GAN) model. This model is trained using a dataset of printed circuit board (PCB) design images and their corresponding actual printed scans. By doing so, the GAN generates a predicted output of what a test PCB design will look like when printed.

After obtaining the predicted scan from the GAN model, we apply a series of metrology algorithms to assess the gap and width of the printed tracks. These measurements are crucial in determining the electrical characteristics of the printed components. The resulting data on gap and width are then fed into a machine learning model that has been trained with a variety of resistance values corresponding to different gap and width configurations.

This process allows us to estimate the resistance value of a predicted printed scan accurately. By incorporating ML models in our fabrication workflow, we can significantly reduce trial-and-error and improve the quality of printed electronics, leading to more reliable and efficient production.

Individual Contributions

This project was extensive and required expertise in a variety of domains with high dependency between tasks, therefore, we believe that it was definitely a joint effort which meant that every individual supported others and offered help in tasks that were not designated to them entirely. The tasks were designated to each individual keeping in mind their expertise and interest. Focusing on the individual focus areas of the team members, here's the individual contribution of each member.

Hardik Hedaoo worked on the metrology algorithm, focusing mostly on image processing and edge detection to analyze the printed cells. He focused on identifying ways to measure the gaps and widths of the components. Managed the orientation of the printed electronic scans with Geegah. Based on the metrology, he successfully prepared the image data that was used to train the GAN Algorithm and the tabular data for Machine Learning Model.

Aditi Rao designed the metrology algorithm to get the edge and contour detection to compute the widths and the gaps. She has expertise in Deep Learning algorithms, hence, she played a pivotal role in designing and training the GAN model. She did thorough research on the suitable methods and algorithms for our problem statement. She modified the algorithm to achieve gaps and contours for conjoined components and several files.

Syed Askari Raza managed the orientation of the printed electronic scans with Geegah. He laid the foundations of the ML model. He managed to achieve the dataset for the training and testing of the models. He successfully brainstormed, designed, and trained the Machine Learning model to predict resistance. Using this model, he demonstrated accurate prediction of resistance of the PCB designs.

Haochen Luo focused on ensuring that the printing was timely completed. Since the pivotal point of this project was to get the prints of electric components, he ensured that the PCB designs were made timely and printed for the rest of our team to initiate metrology and Deep Learning.

TABLE OF CONTENTS

1. Introduction

Printed Electronics (PE) represents a significant advancement in the manufacturing of electronic components, offering a cost-effective and flexible alternative to traditional fabrication methods. This technology enables the production of electronic devices on a variety of substrates, including flexible materials, which has led to the emergence of flexible hybrid electronics. These innovations are pivotal in developing lightweight, bendable, and portable devices that can be used in new and diverse applications, ranging from wearable technology to large-area sensors.

Despite its numerous advantages, the PE production process is fraught with challenges, primarily due to its instability during the printing phase. The quality and functionality of printed electronics can be greatly affected by factors such as the viscosity of inks, the interaction between the ink and substrate, and environmental conditions during the printing process. These factors can lead to variations in circuit patterns, conductivity, and overall device performance, making the output often unpredictable.

The instability of PE printing arises from several sources: the non-uniform distribution of ink, drying rates that vary with environmental conditions, and mechanical stresses that occur during the drying and curing phases. These issues underscore the need for precision and control in the manufacturing process, which are currently lacking in conventional PE production methods.

To address these challenges, there is a growing reliance on machine learning techniques to enhance the predictability and reliability of printed electronics. By applying advanced algorithms and data-driven approaches, it is possible to analyze and predict the behavior of inks and substrates under different conditions, thereby optimizing the printing process and improving the quality of the final product.

The importance of improving PE lies not only in enhancing the quality and performance of the devices but also in ensuring the scalability and economic viability of this technology. As the demand for more sophisticated and reliable electronic devices grows, the ability to produce high-quality printed electronics efficiently and consistently becomes crucial. Through the integration of machine learning models and the continuous study of PE dynamics, we aim to overcome the existing limitations and unlock the full potential of this promising technology.

2. Design Problem

The most significant advantages of printed electronics are similar to those of 2D printing: flexibility, no need for mass production to reduce costs, and the ability to miniaturize to the individual user. However, current PE technology is very unstable, making the printed result too far from the design expectation, or even unusable. This would waste a large amount of material and money, preventing the core advantages of PE technology from providing benefits. Therefore, how to reduce the instability of current PE technology, is the design problem of this project.

From the beginning of the project design, the instability consists of two aspects. They are the difference in geometry between the design and printing results, and the difference in electrical properties. In which, the difference in electrical performance is further analyzed based on the difference in geometry. These two types of uncertainty are specifically analyzed with different focuses:

1. Instability of geometry shape
    1.1. Same ink, same print parameters, different print targets.
    1.2. Same ink, different print parameters, same print targets.
    1.3. Different ink, same print parameters, same print targets.
    1.4. The combined effect of multiple differences.

2. Instability of electrical properties
    2.1. The value of the resistance
    2.2. The value of the capacitance

Based on these two uncertainties, how to use these data to optimize the current PE technology is also part of this project:

3. Use of instability data
    3.1. Modeling of input settings and printed geometric results.
    3.2. Modeling of geometric results and electrical properties of prints.
    3.3. Inferring required changes to input settings based on the model and design requirements.

In the original plan, 1.1, 1.2, 1.3, 2.1, 2.2, 3.1, and 3.2 were all clearly stated goals that were expected to be collected and completed by the test. However, the project was part of a large cross-campus collaborative program with a complex process. Combined with the funding not being available until the second semester, many of the targets could not be met. By the deadline, our group was only able to complete 1.1, 2.1, 3.1, and initial testing of 1.2 and 3.2 using the corresponding data from last year's old design.

In details, the final problems involved in the project were:

1. Measured the differences in image geometry between different design goals and print results with the same ink and the same printer input parameters (1.1).
2. Trained Generative Adversarial Network (GAN) models using normalized images of design targets and print results to model the relationship between input parameters and print result images (3.1).
3. Using resistance data measured over the last year (2.1), including a small amount of data from different printer input parameters (1.2), initially explored a model of the relationship between the scanned images of the print results and the actual electrical performance of the print results using Machine Learning (3.2).

3. System of requirements

For measurements, the measurement process should be normalized enough to accommodate different measurement objects.

For models, the model should be able to receive continuous inputs and outputs.
For images, it should be able to relate to actual physical dimensions.
For training, generalizability should be guaranteed.

Volterra V-One an extrusion printer and BotFactory SV2 an ink-jet printer are used for printing the Components for this project. Extruded tracks offer lower printing resolution, but better electrical characteristics compared to inkjet printed tracks.

The Voltera V-One PCB printer is a desktop-sized prototyping tool that drills through-holes, prints traces using conductive ink, dispenses solder paste, and has a built-in reflow bed. Test ideas quickly and iterate within hours.

The Botfactory SV2 inkjet prints low-resistivity conductive inks and dielectric insulating inks to make Printed Circuit Boards (PCBs) in minutes on a variety of stiff and flexible substrates. It sequentially prints conductive traces and insulating layers, building vias in the dielectric layer to interconnect layers.

4. Range Of Solutions

GAN

- Pix to pix

The foundational approach to image-to-image translation is detailed in the paper "Image-to-Image Translation with Conditional Adversarial Networks." This study introduces a versatile framework employing cGANs, which are adept not only at learning the mapping from input to output images but also at autonomously determining the loss function necessary for such transformations. The authors leverage a "U-Net" architecture for the generator and a "PatchGAN" design for the discriminator, a setup proving robust across various applications such as photo generation from label maps, image colorization, and object reconstruction from edge maps. The effectiveness and adaptability of this framework are well-documented, highlighting minimal need for parameter tuning while providing extensive qualitative results that demonstrate its performance.

In our explorations, we have discussed several extensions and variations of this core methodology to cater to specific project needs. We considered incorporating additional parameters such as resistances and capacitance into the Pix2Pix model, which would require modifications to the input layer of the generator to accept both image data and these numerical values. This adaptation aims to enrich the model's input, providing a more detailed context for image generation tasks, particularly in technical fields where such parameters are relevant.

Further, we explored alternative models like CycleGAN for scenarios where paired training data is not available, and StyleGAN for high-resolution image generation. Each of these models offers unique benefits: CycleGAN facilitates the translation between two unpaired image domains, and StyleGAN generates photorealistic images with fine control over the generation process through style-based architecture.

These explorations underscore the broad applicability of cGANs and related architectures in tackling a diverse range of image-to-image translation tasks, each with distinct requirements and challenges. The continuous evolution of these models opens up new possibilities in artificial intelligence, pushing the boundaries of what can be achieved in various applications of image synthesis and modification.

ML

- Lasso
- NN

Linear regression is employed as the machine learning model due to its simplicity and proven track record in predicting outcomes where the relationship between variables is linear. This model offers excellent interpretability, as each coefficient indicates the expected change in the dependent variable resulting from a one-unit change in a predictor, holding all else constant. It's also computationally efficient, allowing for quick training and prediction, which is essential for applications needing real-time operations. Additionally, linear regression is less susceptible to overfitting, particularly when the model is appropriately regularized or when the number of predictors is kept in check relative to the sample size. It serves as a fundamental tool in predictive analytics, often used as a benchmark to evaluate the performance of more complex algorithms. Due to its widespread application across various fields—from economics to engineering—linear regression is a reliable choice, ensuring that the move to more sophisticated models is justified by significant improvements in performance. This approach ensures that the project maintains a balance between simplicity and the capacity for detailed predictive insights.

5. Design and its Implementation.

Our GAN model was trained on a dataset consisting of PCB design images and their corresponding scans after printing. This training process enabled the GAN model to learn the relationship between the original PCB design and the resulting printed product.

Using this trained GAN model, we could predict the expected outcome of a given PCB design, allowing us to simulate the printing process without actually creating the physical component. This simulation capability was crucial for evaluating the quality of the design and identifying potential issues before proceeding to the actual printing stage. The GAN Image generation algorithm serves as a digital twin to the actual printing process and is basically a visualization of the likely print that the electronics printer will be generated.

We applied a series of metrology algorithms to analyze the predicted scan. These algorithms allowed us to measure key attributes such as gap width, trace thickness, and overall layout accuracy. By comparing these attributes with the original design specifications, we could identify deviations or inconsistencies that might affect the performance of the final PCB.

After assessing the predicted scan, we focused on determining its electrical properties, specifically resistance. To achieve this, we developed a machine learning (ML) model that was trained on a dataset containing various PCB designs, their gap widths, and corresponding resistance values. This ML model was designed to predict the resistance of a given PCB based on the observed gap and trace widths.

Using the data derived from the metrology analysis, we input the gap and width information into our ML model. The model then provided an estimated resistance value for the predicted PCB. This resistance estimation was critical for understanding the electrical characteristics of the design and ensuring that it met the required specifications for functionality and safety

5.1 Metrology :

The metrology procedures in this project serve the purpose of processing prints and identifying their likely dimensions and building a relationship with the electrical properties of the printed electronic components. The metrology involves image processing and computer vision techniques to improve the quality of scans. The cleaned scanned images of the printed electronics are then processed further to calculate the likely dimensions such as width and gaps in the electronic components. This section highlights multiple steps in this process. The primary function of this stage within the project is to prepare the images for the Generative Adversarial Network based image generation and to calculate the dimensions of the electronic components. The figure below demonstrates the width and gap dimensions that we're exploring along with some components of the prints that we will address:

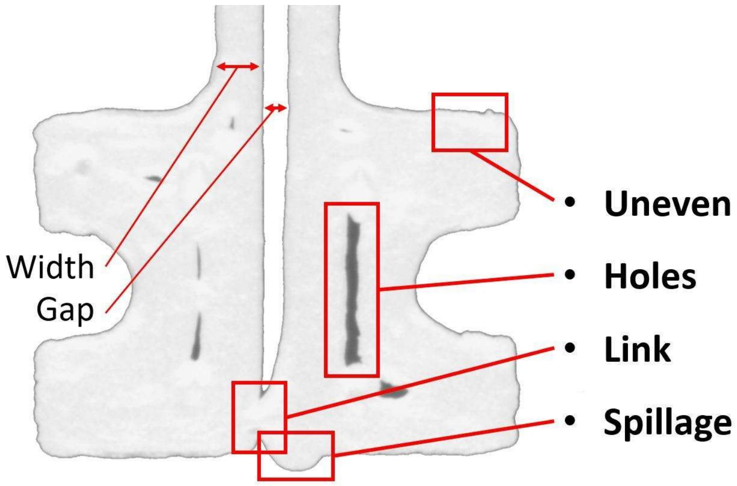


Fig 1. Printed PCB component indicating width, gap and irregularities that occur during printing

5.1.1 Preparation of printed electronic cell Images

The first step is to analyze the nature of image data that we have available of our printed electronic components and to formulate it in an appropriate way that enables the analysis of dimensions, edges, gaps, and ink spreads. The PCB design was printed using Volterra V-One Printer and we successfully completed multiple iterations of printed electronic components. Once these cells were printed, we scanned the newly printed PCBs using the Voltera V-One extrusion printer and BotFactory SV2 inkjet printer at Cornell SonicMEMS Lab. The scanner thoroughly scans the image at a resolution of 4800 dots-per-inch. The interpretation of this resolution is that the scanner generates an image that has 4800 pixels in each dimension representing a length of 1 inch. This specification is of utmost importance as it will be used in the future to find the dimensions like widths and gaps using this pixel to millimeter conversion. The scanned PCB circuits obtained from the scanner are as show below:

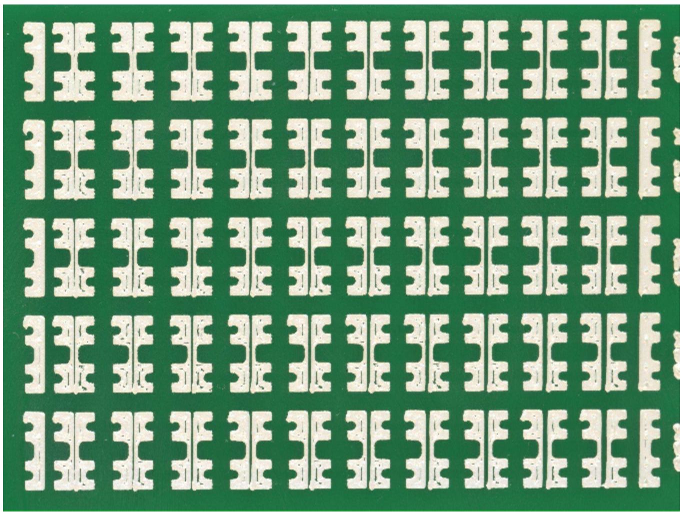


Fig 2. Scanned PCB circuits obtained from the scanner

These scanned images were processed with the help of computer vision techniques. The first step was to generate these images in greyscale. This way, we were able to differentiate the substrate (green base) from the actual prints. The grayscale conversion was followed by thresholding the image at a value of 125. This separates the background from the foreground objects which happen to be the printed cells. The grayscale and thresholded images are as show below:

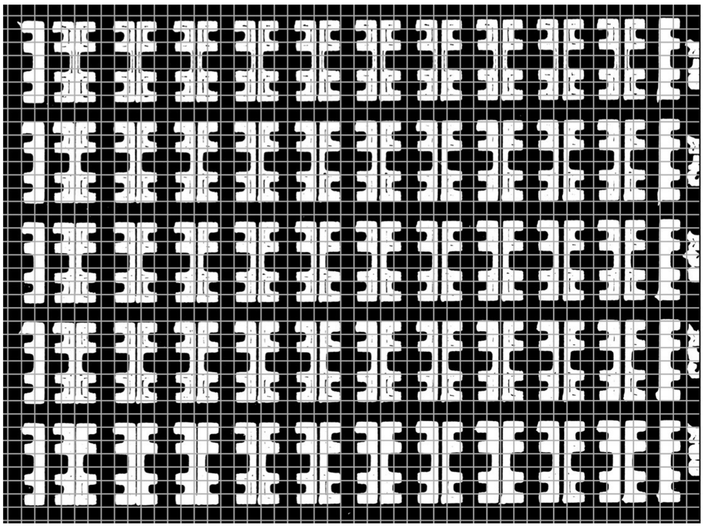


Fig 3. Greyscale Thresholded Images of Scanned PCB circuits

This binary image is then cropped to separate each cell as a separate image for processing of each individual printed electric cell. The cropped images of each cell are then subjected to the Center of Mass adjustment and standardization of the resolution of the image. The center of mass is adjusted to keep the foreground in the center and the standardization of the images is done by adding padding to the borders of each image to prevent any kind of interpolation of the foreground pixels which makes it vulnerable to inaccurate measurements of the dimensions. A sample final standardized image generated for a cell is demonstrated below:

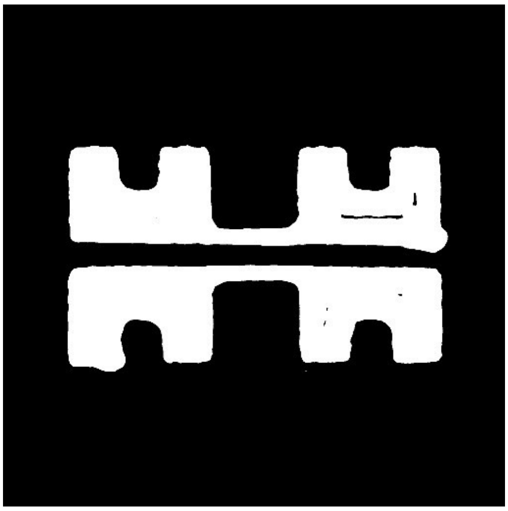
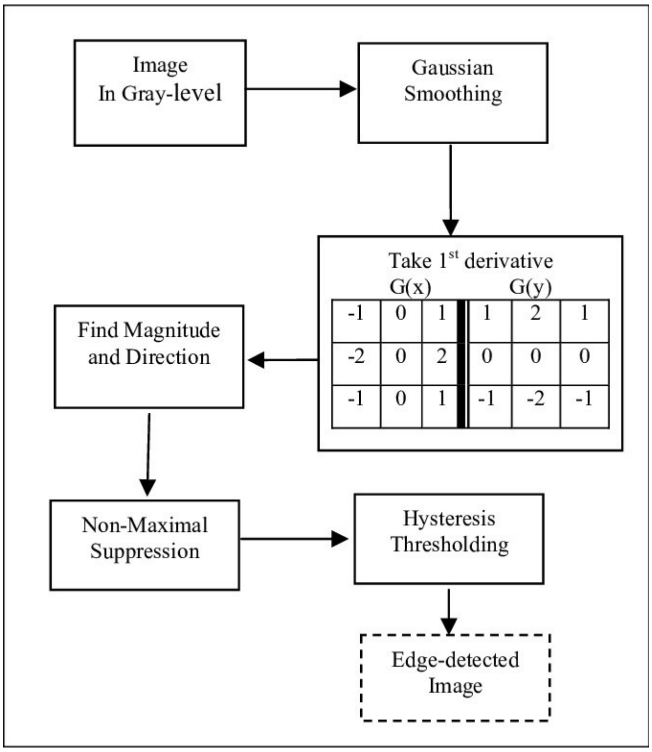


Fig 4. Standardized Generated Image

These final cell images have a resolution of 512 x 512 since this is the resolution that enables accurate and efficient implementation of Image to Image translation algorithm we will apply in the next part of this project. These images are then subject to comprehensive processing in order to extract out information like dimension sizes.

5.1.2 Detecting Electronic Cells by Edge Detection

This stage of the task hold utmost importance as here we will apply computer vision techniques to identify dimensions like the gap between sub cells which correspond to the capacitance of this component as well as the width of each subcell to determine the likely resistance in these components. To do this, we first apply the Canny Edge detection algorithm to each cell image. Canny edge detection is generally used to identify edges in images by detecting areas where intensity changes rapidly. This is a multi step algorithm that uses Gaussian filters to remove noise, gradient calculation using Sobel operators, and non maximum suppression to thin the edge. The workflow of Canny edge detection is shown as below:



-1	0	1	1	2	1
-2	0	2	0	0	0
-1	0	1	-1	-2	-1

Fig 5. Canny Edge Detection Flowchart

The canny edge detector accurately detects the edges of each subcell and uses this edge detection to plot a green outline around each subcell. The coordinates of these edges will help us determine the dimensions. The contour plot after edge detection is shown as below:

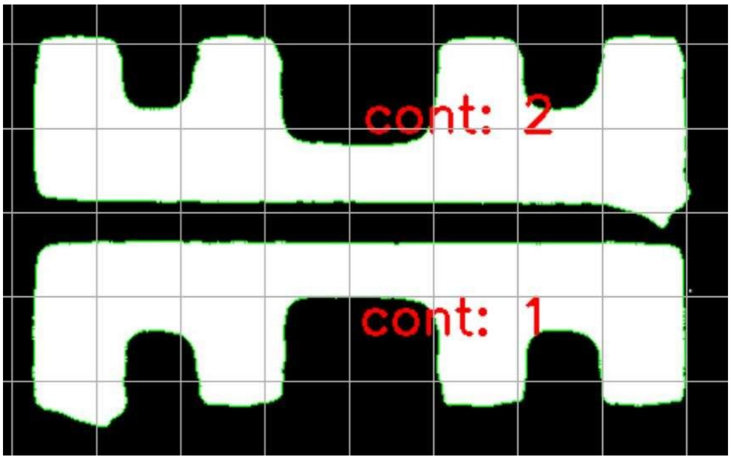


Fig 6. Contour Detected Components

As we see the green outlines made, we will use these coordinates to determine gaps between sub cells and the thickness and width of each sub cell. The respective sub cells are also labeled as a unique contour. The most important thing to note in this sub task is the set of x and y coordinates collected for both the contours which will help in comparing them for dimension sizes. The next sub task highlights this process.

5.1.3 Dimension Size Computation

This step helps us achieve approximate width and gaps for each electronic cell that were printed using Voltera V-One and Botfactory SV2 printers in the Cornell SonicMEMS Lab. We start by computing the gap between sub cells. At each X coordinate along the frame of the image, we compare the difference in y coordinates along the edges of both sub cells. The gap between the two edges is demonstrated in the scatter plot below:

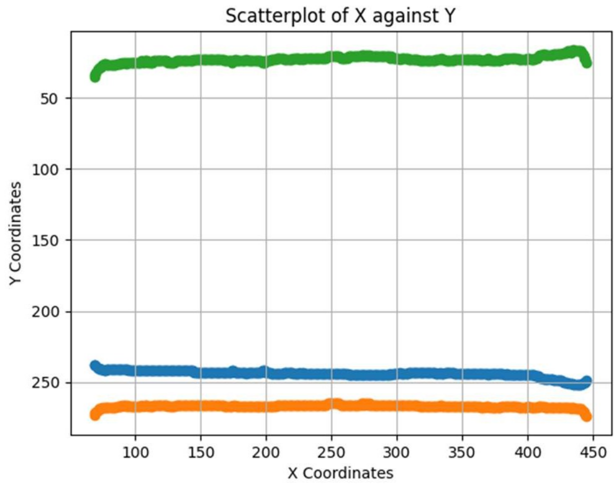


Fig 7. Scatter plot of Gaps between Edges

Using this difference, we determine the distance between the two cells in y direction but in terms of pixels. The use of scanner resolution of 4800 dots-per-inch is used to convert this pixel unit into millimeters. The images generated for each cell initially had a resolution of 2048 x 2048. However, to generate images that could be used in the Generative Adversarial Network for predicted print image generation, we interpolated the image to 512 x 512 and adjusting the pixel-to-millimeter ratio within our Python Script as shown below:

```
def pixel_to_distance(distance):
    conversion_factor = 4800/(4 * 25.4) #4800 dpi converted to 4800dots per mm

    dist_in_mm = []
    for i in range(len(distance)):
        new_dist = abs(distance[i]/conversion_factor)
        dist_in_mm.append(new_dist)

    return dist_in_mm
```

Fig 8. Pixel to mm conversion code

A resolution of 4800 dots-per-inch corresponds to 4800 dots for every 25.4 millimeters and since we interpolated our image by a ratio of 1:4, we adjusted this ratio in our python function to extract the gap in millimeters. The outcome of this function is demonstrated below:

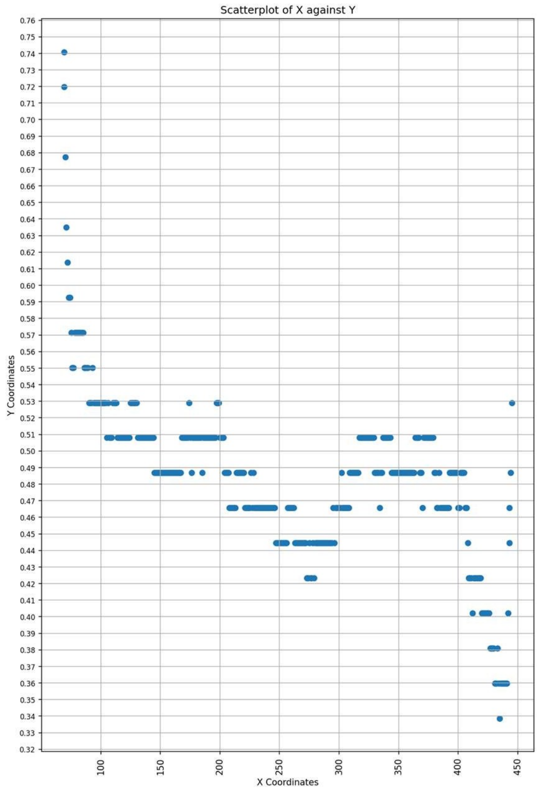


Fig 9. Scatter plot of gaps between edges along length.

This plot demonstrates how the gap between the edges of the two sub cells vary along their lengths.

5.1.4 Computing Width of Sub cells

The scope of this project extends to exploring the possibility of predicting resistance of the cells based on their thickness or width. For this, we perform similar processing techniques to identify the thickness of each sub cell which is deterministic for its resistance. The same set of procedures were followed to separately determine the width of each sub cell of a printed component.

5.1.5 Desired PCB Design Analysis

The metrology functions as an important task for generating predicted print images from the desired PCB design layout and to find dimension sizes to predict the Electrical properties of the printed components. To efficiently implement Generative Adversarial Network to Image-to-Image translation, we processed the PCB design layouts to ensure that the input image data for training of GAN model is as efficient as possible.

The PCB designs that are printed using Voltera V-One and Botfactory SV2 printers were designed on Altium, a well known software to design PCB and circuit boards. The design layout is demonstrated below:

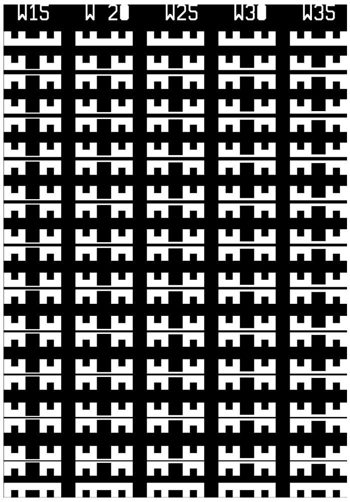
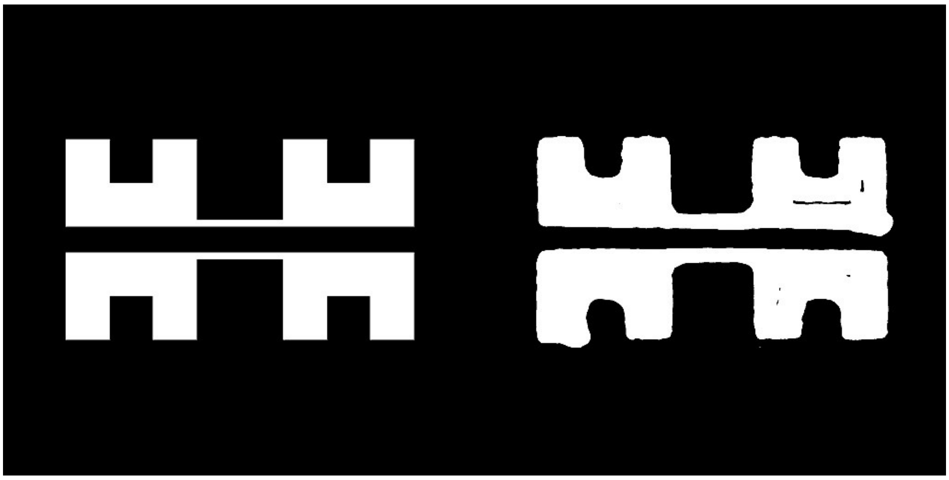


Fig 10. Desired PCB Layout

This PCB layout design is processed in a similar way. The images are cropped to extract separate images of each cell. The cells are identified using edge detection techniques and then standardized at a resolution of 512 x 512. Our dimension computation algorithm concluded that the size of dimensions in these images mapped to millimeters match the dimensions at which these cells were made on Altium. The width of these cells vary from 150mm to 350mm (going from left to right) and 600mm to 200mm (going from top to bottom). The significance of this sub task is to prepare image data for our GAN model in which the PCB design layout images serve as the input in the training data whereas the actual print scans are used as the output in the training data. The following step was thorough data augmentation of the cell images in which multiple orientations of the images were made which helps us increase data size and also enable more generalization in the model.Moreover, scaling and center of mass adjustment was done to allow efficient mapping of the model to the real world prints. Each of these cell images were also generated with 90 degree rotations increments to efficiently train our Deep Learning Algorithm. A training data point contains a set of input variables/features and output or target variables. The image below shows the pair of input and out images used in the next task.



(a) (b)

Fig. 11 - Inputs of the GAN model

a) Desired PCB Layout b) Actual Printed Scan

The image of the left is the desired electric component to be printed and is a design of the component made on Altium. The image on the right shows the actual print that was scanned and retrieved as an image after thresholding and processing. These image pairs will serve as training data for the Deep Learning GAN Model.

5.1.6 Preparing Dimensions Data for Resistance Prediction (ML)

The final sub task of metrology is to use our edge detection and dimension retrieval algorithms to extract measurements for all the cells that were printed. To extract maximum information about the width and gap dimensions, we retrieved averages, standard deviations, peak values, and the average of these parameters for each quartile of the length along the prints and the PCB design layouts. These features were exported as a DataFrame using the Pandas framework in Python and were exported as a Comma Separated Value file to use in the final step of this project which is using Machine Learning to predict resistance of a printed component based on its dimensions.

5.2 Generative Adversarial Network Pix2Pix :

The GAN model uses the pix2pix method and is trained by metrology-based PCB images. It can find the pattern in scanned images, output predicted images with given data, such as gaps and widths.

The ML model utilizes width and gap data from a metrology algorithm and electrical data from each print as training data. It predicts the electrical parameters for a new test image based on the given metrology parameters.

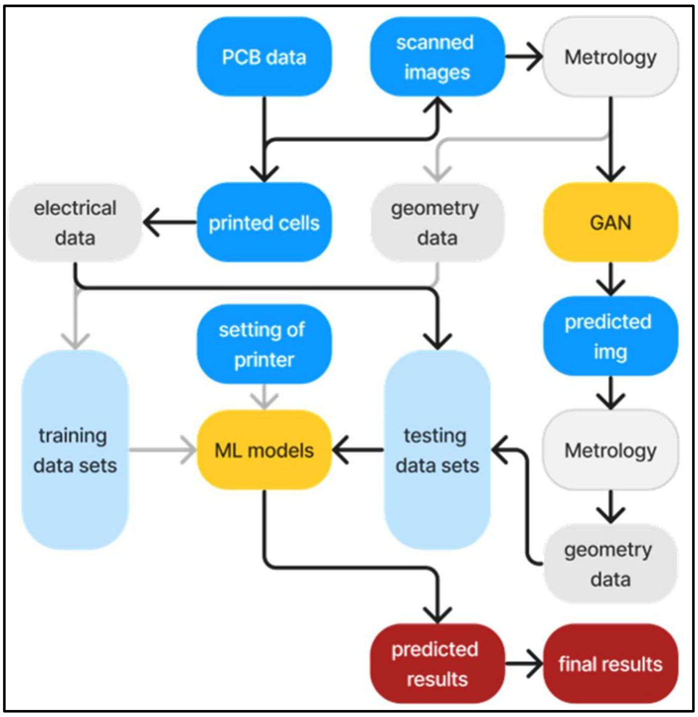


Fig 12. - Implementation Flow Chart
(Gray for metrology and direct data result. Yellow for models.)
(Deep blue for data sources. Light blue for datasets. Red for results.)

5.2.1 Pix2Pix Algorithm:

Pix2pix is a conditional Generative Adversarial Network (GAN) architecture used for a variety of image-to-image translation applications. It is made up of two main parts: a discriminator and a generator, which work together to produce the intended result.

With Pix2pix, the generator is in charge of producing realistic images based on a specified input called the "layout." Usually, this arrangement acts as a blueprint to direct the generating process. In order to improve the robustness and provide unpredictability to the created pictures, the generator also includes Gaussian noise. The net could still learn a mapping in the absence of Gaussian noise, but it would only be able to match a delta function as a distribution since it would generate deterministic outputs

The discriminator is essential for determining the accuracy of the produced pictures. In order to discern between synthetic and actual image-layout pairings, it makes a distinction between the two. The discriminator's job is to give the generator feedback so that it can produce outputs that are more believable.

The generator maximizes the possibility that the discriminator would classify something incorrectly during the training phase.The generator aims to produce pictures that are identical to the genuine ones, deceiving the discriminator. The discriminator should ideally be able to consistently distinguish between genuine and created pictures when its chance of accurately classifying false images is around 50% representing a great balance.

Image-to-image translation problems are common in image processing, computer graphics, and computer vision. They involve transforming one representation of a scene into another using convolutional neural networks (CNNs). Despite the fact that their shared purpose is to forecast pixels from pixels, each job has traditionally used different approaches. Crafting good loss functions for CNNs requires extensive manual work, which frequently results in fuzzy outputs.

Generative Adversarial Networks (GANs) provide a solution by training a generative model and minimizing a discriminative loss function while penalizing fuzzy pictures. We investigate Conditional GANs (cGANs) for image-to-image translation problems, in which a conditional generative model is trained on an input picture and outputs a matching image.

To put it briefly, Pix2pix converts input layouts into realistic pictures by utilizing a conditional GAN architecture that includes a generator and discriminator. The generator gains the ability to generate outputs that are persuasive through adversarial training, and the discriminator offers input to help it become better. Pix2pix is a flexible and efficient solution for a range of image translation jobs since it incorporates Gaussian noise, which improves the quality.

5.2.2 Pix2Pix in Printed Electronics

As we've built on the metrology, we saw that the extensive image processing is done to be able to somehow predict the printed cell before the actual printing has been initiated for a certain PCB layout. This is primarily due to the extensive times and costs associated with inefficient printing that leads to undesired electrical properties. Therefore, we implement the Pix2Pix algorithm to have the ability to be able to predict the type of print that will be generated for a PCB layout in order to optimize the design before initiating the printing. The tasks performed in metrology generated standardized images of PCB design and the actual prints. These images were processed to generate multiple orientations for the sole purpose of training our Pix2Pix algorithm. The workflow of this algorithm with respect to our data is represented below:

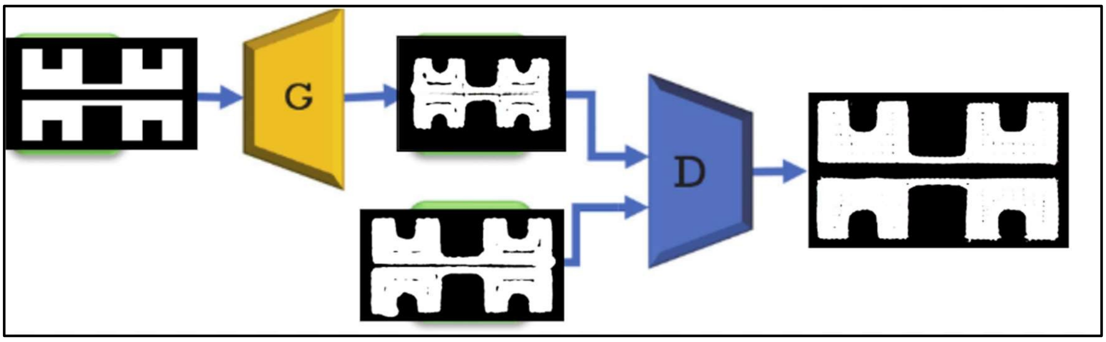


Fig13. GAN Model Workflow (includes Generator and Discriminator)

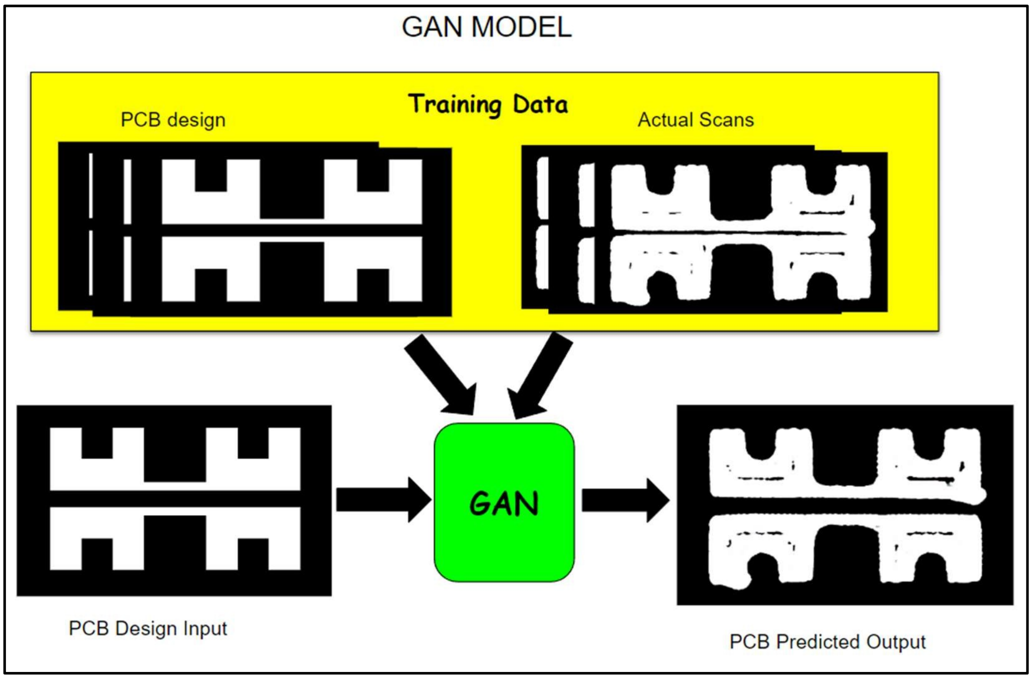


Fig14. GAN Model Workflow
(Depicts Training Data , Input Data and Output of the GAN)

5.2.3 Pix2Pix Functionality

The Pix2Pix Algorithm was visualized on an open source platform called wandb. Pix2Pix algorithm computes images which are in essence matrices of pixel values. Therefore, the computation requirements are high, for which, the training of the model was done on the GPU enabled servers in Cornell SonicMEMS Lab that were requisite to our team. On the completion of training, we tested the performance of the model for which we input a sample test image which was a cell with width of 200 millimeters and gap of 600 millimeters. The output can be seen below:

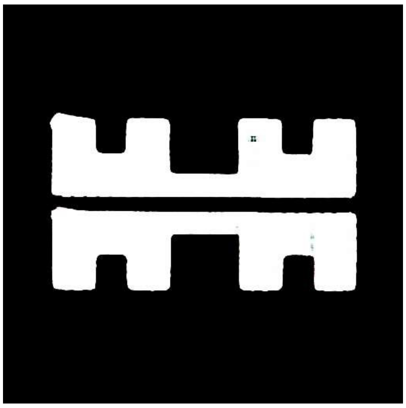


Fig15. Predicted Pix2Pix Output

5.3 Machine Learning to predict Resistance:

In our methodology, we aim to use the measured thickness/width of printed cells and deviations in it to predict its resistance. The primary aim of this project is to optimize the PCB layouts in a way that they print components that can achieve the right electrical properties like resistance and capacitance. Therefore, we look to achieve this by predicting the resistance of a component likely to be printed for a certain PCB design layout. As discussed earlier, we used metrology to find thickness and width measurements in millimeters of each printed cell. These measurements include the average width along the length of a sub cell. Alongside, we also retrieved standard deviation, and peaks noticed in the prints due to ink spread or discontinuity in extrusion. We use a machine learning (ML) model based on linear regression for predictive analysis. The major goal of this ML model is to forecast resistance values based on the gaps or widths recovered from printed circuits using a metrology approach.
After all the metrology and processing, we obtained two width values, the feedrate, and the corresponding resistance values corresponding to each cell. This dataset can be viewed as a simple regression prediction. This is a traditional machine learning application with multiple models to choose from.

	A	B	C	D
1	avg_bottom_width	avg_top_width	feed_rate	resistance
2	0.31842029	0.342961353	500	0.04258566
3	0.31842029	0.342961353	500	0.04043445
4	0.305229469	0.32026087	500	0.04194488
5	0.305229469	0.32026087	500	0.04083287
6	0.313818841	0.354004831	500	0.03406928
7	0.313818841	0.354004831	500	0.03763941
8	0.369342995	0.384374396	500	0.02713487
9	0.369342995	0.384374396	500	0.02881878
10	0.326702899	0.353391304	500	0.0419332

Fig.16 The dataset for ML models

Therefore, we batch tested a variety of models including linear regression, polynomial regression, lasso, lasso polynomial and neural networks.

5.3.1 Mean Squared Error based Linear Regression

The model learns to map these features to the output labels (resistance values) by finding the best-fit line that minimizes the error between predicted and actual resistance values. This involves calculating the optimal coefficients (weights) for the linear equation:

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n$$

Here, $\hat{y}$ is the predicted resistance value, β_0 is the intercept, and $\beta_1, \beta_2, \ldots, \beta_n$ are the coefficients for the input features $x_1, x_2, \ldots, x_n$.

For the components that we printed, we have the hardware and capability to measure their resistance values that have been recorded. These resistance values tend to be our target variable or output variable. The input features are segmented into measurements of widths and print parameters such as extrusion rate and feed rate. A total of 400 cells were printed for which we retrieved all input variables alongside resistance measurements that would be the output variable. Based on our trained Machine Learning model, we can easily predict what the resistance of an electrical component will be.

During the training step, the ML model is trained with the widths or gaps of the printed electronics, which are recognised and quantified by the metrology method, as input. Simultaneously, the resistance values linked with these widths or gaps are used as output labels for training.

In the assessment step, the ML model is tested against expected scans generated by another model, especially a Generative Adversarial Network (GAN). These expected scans serve as test images. In this case, the widths and gaps recovered from the projected scans serve as input characteristics for the ML method.

The ML algorithm then takes these input features, which represent the gaps or widths of the expected scans, and applies the information gained during the training phase to predict the appropriate resistance values. This prediction method is based on the patterns and correlations acquired from the training data, allowing the machine learning algorithm to generate resistance value estimates for the supplied inputs.

In this algorithm project, during the training phase, Mean Squared Error (MSE) aims to find the values of the coefficients β that minimize the residual sum of squares (RSS), which is the sum of the squared differences between the observed y and ŷ values:

$$\mathrm{RSS} = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

5.3.2 Model Design

The Machine Learning model was implemented using a number of software systems. Primarily, the training was done on a GPU enabled personal computer using Visual Studio Code. The relevant frameworks employed included OpenCV which is used for image processing and analysis. Moreover, Numpy, Pandas, and Sci-kit frameworks were used for training and testing of the model. In our methodology, we employ a linear regression model for predictive analysis, focusing on forecasting resistance values based on gaps or widths in printed circuits. These geometrical features are quantified using a metrology approach. The process involves two main steps: training and assessment.

- Training Phase
  - Input Features: Widths of printed electronics, quantified by a metrology method. Print parameters like feed rate.
  - Output Labels: Corresponding resistance values for these widths.
  - Model Training: The input features (widths or gaps) are fed into the linear regression algorithm. The model learns to map these features to the output labels (resistance values) by finding the best-fit line that minimizes the error between predicted and actual resistance values. This involves calculating the optimal coefficients (weights) for the linear equation:
- Testing Phase

In the assessment phase, the trained linear regression model is tested using predicted scans generated by a Generative Adversarial Network (GAN). The steps include:

- Prediction:

The linear regression model uses the learned coefficients from the training phase to predict resistance values for the new input features (widths and gaps from GAN scans).

- Evaluation:

The predicted resistance values are compared to the actual values to evaluate the performance of the model. The comparison helps in assessing the accuracy and reliability of the linear regression model. The trained model is evaluated using metrics such as MSE (Mean Squared Error) to ensure it accurately predicts resistance values from the given widths or gaps.

The linear regression model is pivotal in our methodology for predictive analysis of resistance values in printed electronics. By training on the geometrical features (widths or gaps) and their corresponding resistance values, the model learns the underlying patterns and correlations. This learned knowledge is then applied to predict resistance values for new scans, facilitating a comprehensive analysis and understanding of the electrical properties of printed electronics.

5.3.3 Model Evaluation

The final results show that polynomial and lasso polynomial regression work significantly better than the other models.

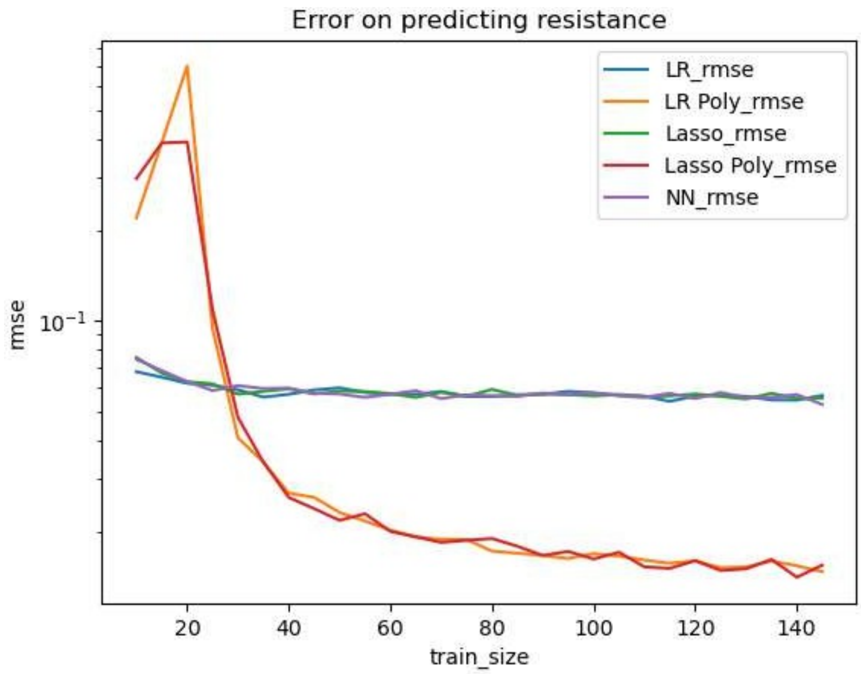


Fig17. Error on predicting resistances by different ML models

The Table1 shows the final detail values for each model:

Table1. Final error for different models

model	Final error
Linear Regression	0.05498159128351664
Polynomial LR (d=3)	0.015505996827501334
Lasso	0.055971187383806076
Lasso Polynomial (d=3)	0.015344379158421306
Neural Networks	0.05785488636220856

The model shows best loss achieved by Mean squared error loss function that uses L1 regularization also called Lasso.

6. Results and Expectations

The integration of artificial intelligence (AI) and machine learning (ML) into the printed electronics fabrication process has yielded significant advancements. The following are the detailed results achieved through our methodology:

- Metrology Algorithm For Training Sets :

The metrology algorithms employed to assess the predicted scans from the GAN model were highly effective in measuring critical attributes such as gap width, trace thickness, and overall layout accuracy. These measurements were consistent with the original design specifications, enabling us to pinpoint deviations that could impact the performance of the final PCB. The accuracy of these measurements was instrumental in ensuring the reliability of the subsequent resistance predictions.

- GAN Model Performance:

The Generative Adversarial Network (GAN) was effectively trained using a dataset of PCB design images and their corresponding printed scans. The GAN demonstrated high accuracy in predicting the outcomes of PCB designs, producing images that closely matched the physical printed products. This capability allowed for precise simulation of the printing process, facilitating the identification and rectification of potential design issues before actual production.

- Metrology Algorithm For Predicted Scans:

The metrology algorithms employed to assess the predicted scans from the GAN model were highly effective in measuring critical attributes such as gap width, trace thickness, and overall layout accuracy. These measurements were consistent with the original design specifications, enabling us to pinpoint deviations that could impact the performance of the final PCB. The accuracy of these measurements was instrumental in ensuring the reliability of the subsequent resistance predictions.

- ML Model Accuracy:

The machine learning model, based on linear regression, was trained with extensive data on gap widths and corresponding resistance values. The model exhibited strong predictive accuracy, providing reliable resistance estimates for new PCB designs based on the geometrical features extracted by the metrology algorithms. This predictive capability significantly reduces the need for trial-and-error in the fabrication process, leading to more efficient and cost-effective production of printed electronics.

- Expectations

Based on the promising results achieved through the integration of AI and ML in our project, we have several expectations for the future impact and applications of this technology.

By leveraging AI models to simulate and optimize printing parameters, our project anticipates achieving enhanced predictability and control over the printed electronics fabrication process, resulting in high-quality, reliable performance. The integration of AI-driven metrology and ML models is expected to improve yield by minimizing defects and reducing material waste, thereby increasing production efficiency and lowering costs. The scalable methodologies developed can be adapted to various applications, facilitating the commercialization of flexible hybrid electronics in industries such as wearable technology, biomedical sensors, and large-area flexible sensors. The project's success underscores the potential for continued innovation through interdisciplinary collaboration, with future research focusing on refining AI models, expanding datasets, and exploring new applications, in partnership with industry.

In conclusion, the integration of AI and ML into the printed electronics fabrication process has demonstrated significant potential to enhance the quality, reliability, and efficiency of production. The results achieved thus far provide a strong foundation for future advancements, paving the way for the broader adoption and commercialization of flexible hybrid electronics.

APPENDIX

7. User Manual :

7.1 Metrology

The first stage of the project is image processing followed by metrology. These tasks were executed primarily using Python frameworks like OpenCV and Numpy. The IDE used for these tasks was Visual Studio Code and the Jupyter Notebook file called 'metrology_and_visualization.ipynb' that visualizes cell images, performs data augmentation, and computes widths and gaps of the cells. This notebook imports cell images for each print iteration, standardizes, crops, and adjusts the Center of Mass. The algorithm then performs edge detection and then computes widths and gaps of the cells. It is followed by a series of visualizations as well. Please note that the notebook takes input of the directory in which the files are stored so that it can access the files and pre-process them.

7.2 Generative Adversarial Networks

The GAN Algorithm is visualized on wand open source platform for Deep Learning. Moreover, the weights are used from pre-trained Pix2Pix algorithms that were obtained from the original implementation of the paper. The training was done virtually on the GPU enabled server in the SonicMEMS Lab.

7.3 Machine Learning Model

The machine learning (ML) model leverages several Python packages, including pandas, numpy, scikit-learn, and matplotlib. Initially, the model ingests a CSV file containing data on width, gaps, standard deviation, average, peak, and feed rate.

The model is trained using this dataset, which includes previously obtained resistance values correlated with the width and gap parameters. The model's performance is then evaluated using Mean Squared Error (MSE) as the metric.

Subsequently, the model applies the width and gap parameters of the predicted scan as test data. It processes this input to predict the resistance based on the training it has undergone.