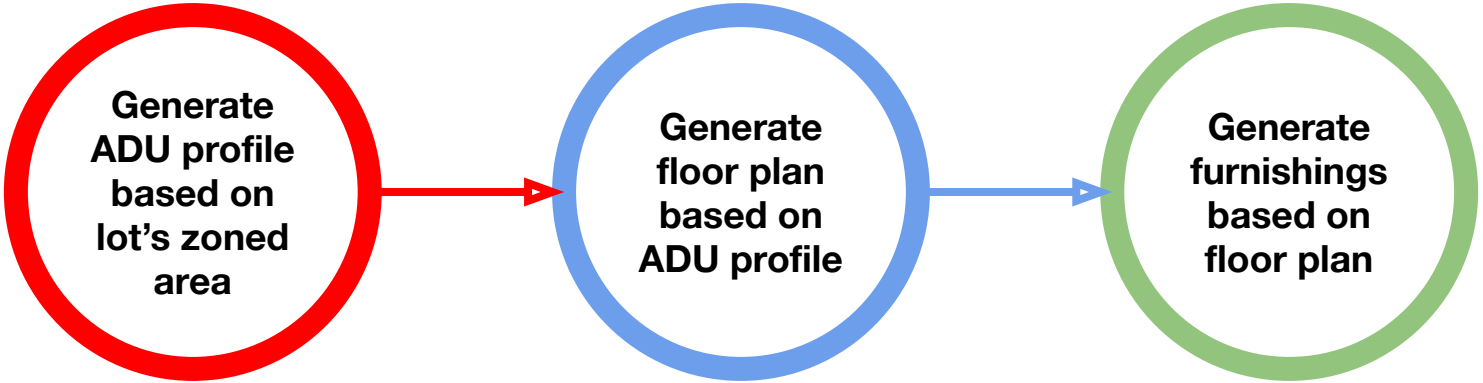
Floor Plan Generation via Generative Adversarial Networks

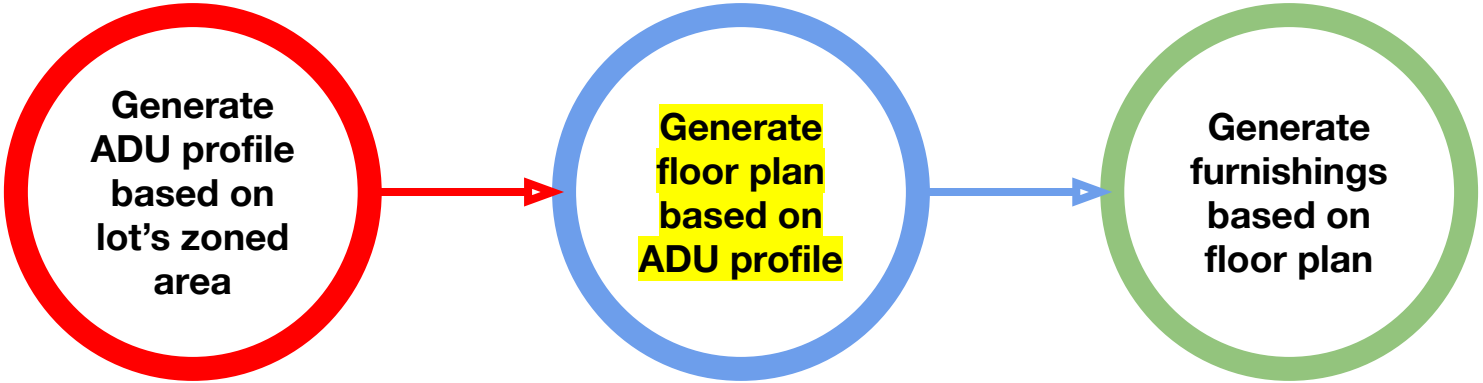
Initial Problem

Assembly Bill 68 has recently passed in California, encouraging residents to build Accessible Dwelling Units (ADUs) on their lots in order to ease California's housing crisis. Can a data model be designed to further expedite this process?

Model Workflow



Model Workflow



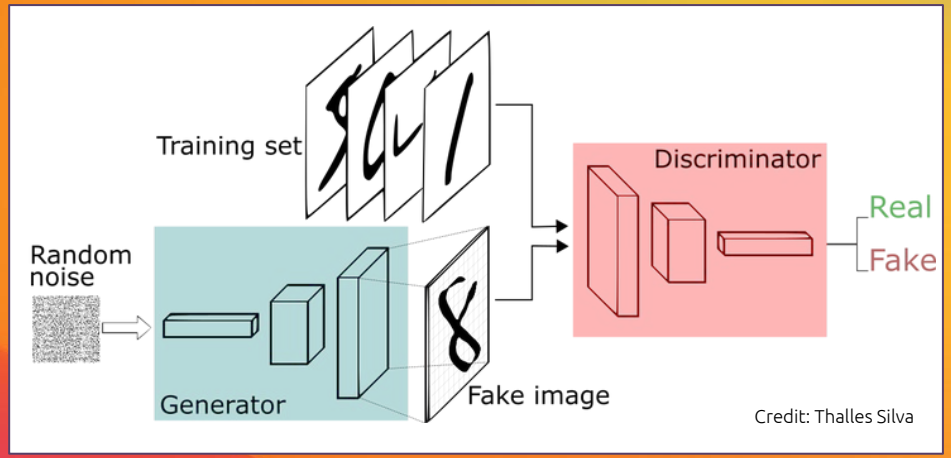
Revised Problem Statement

Can AI be applied to floor plan analysis and generation in order to assist the design process?

- Create a larger quantity of designs
- Give the client a library of choices to create more interest in the process

Generative Adversarial Neural Networks

- Generator - creates “fakes” from the training set
- Discriminator - chooses between real and “fake” and gives the generator feedback
- Generator creates more relevant “fakes”



pix2pix

- Conditional GAN
- Generator uses training data
- Uses L1 and gen/disc loss as internal metrics

Credit: pix2pix Github

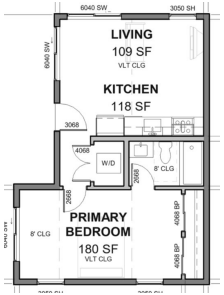
Programming

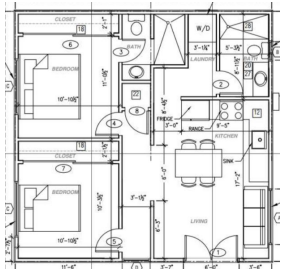
The building’s use, its rooms’ use, and the spatial interplay between rooms

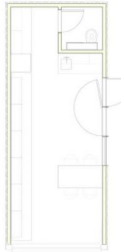
- Specifically looking at ADU programming
- Important metric to judge generated floor plans

Dataset

- 200 Floor plans
- 15 sources
- Buried along other building photos
- No one source big enough for data scraping
- Wide variety of styles







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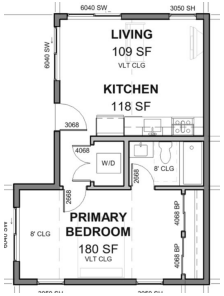

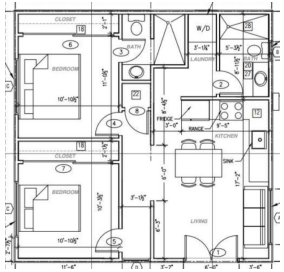

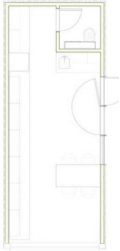

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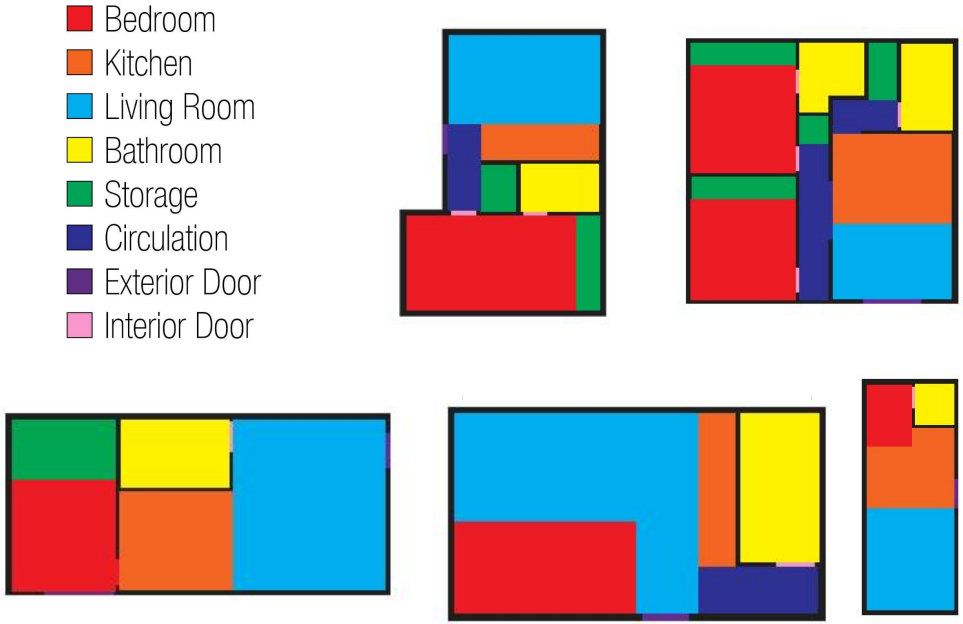


Metrics

Disc/Gen Loss

Neither model should “win”

Spikes are good

log(2) = 0.69. Good reference point for losses

Disc Loss < .69 - Discriminator is doing better than 50/50 at guessing between real and fake images

Gen Loss < .69 - Generator is fooling the discriminator

L1 Loss

As training progresses, L1 Loss should go down

Left vague at what the rate should be

No discernment between any models

Eyeball Test

Most important metric

Images should clean and crisp

Layout should make sense programmatically

Images indiscernible from training image quality

Eyeball Metrics

Poor

Mess of a layout

No ability to tell what rooms should be

Average

Some order programmatically

Rooms consistently not well defined

Good

Good program definition overall, with few obvious mistakes

Only needs quick touch-up to be excellent

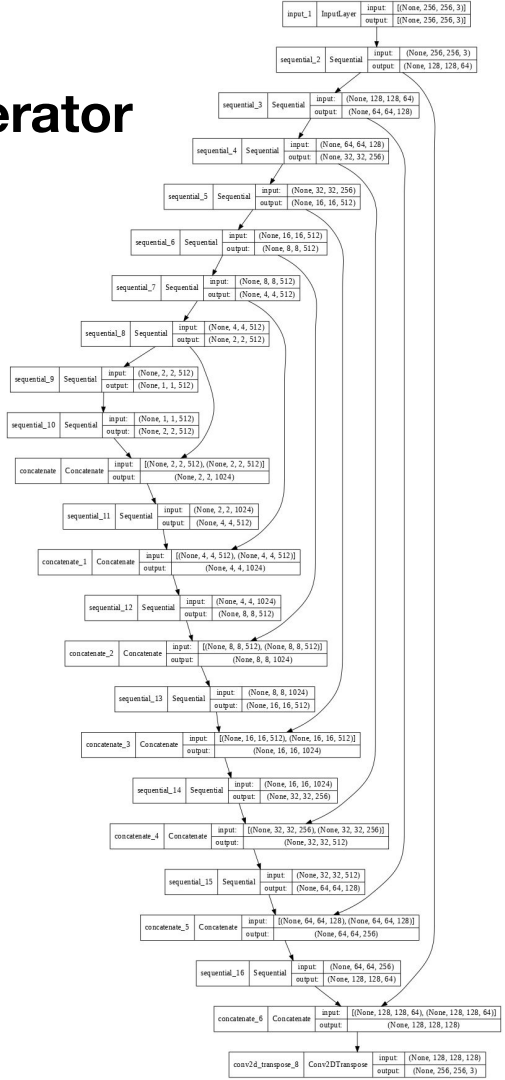
Excellent

Indiscernible from training set

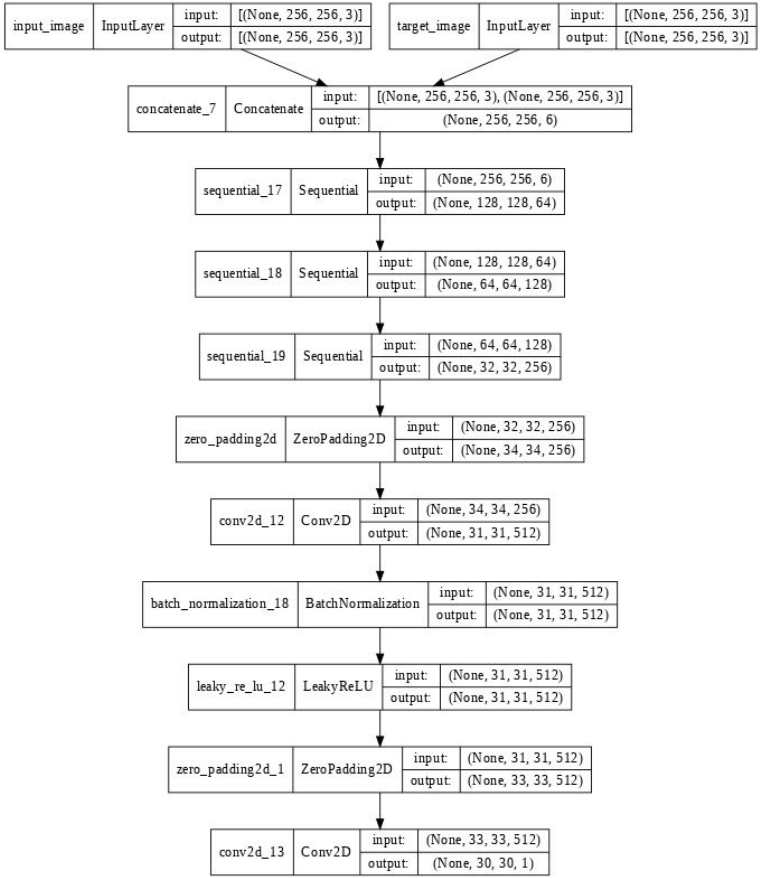
Some smudges acceptable

Could be shown to a client

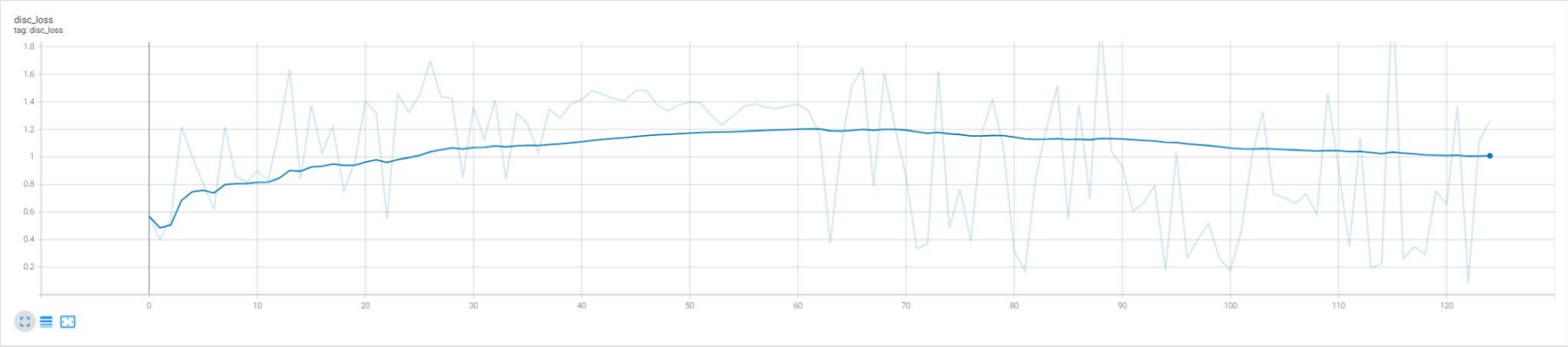
Generator



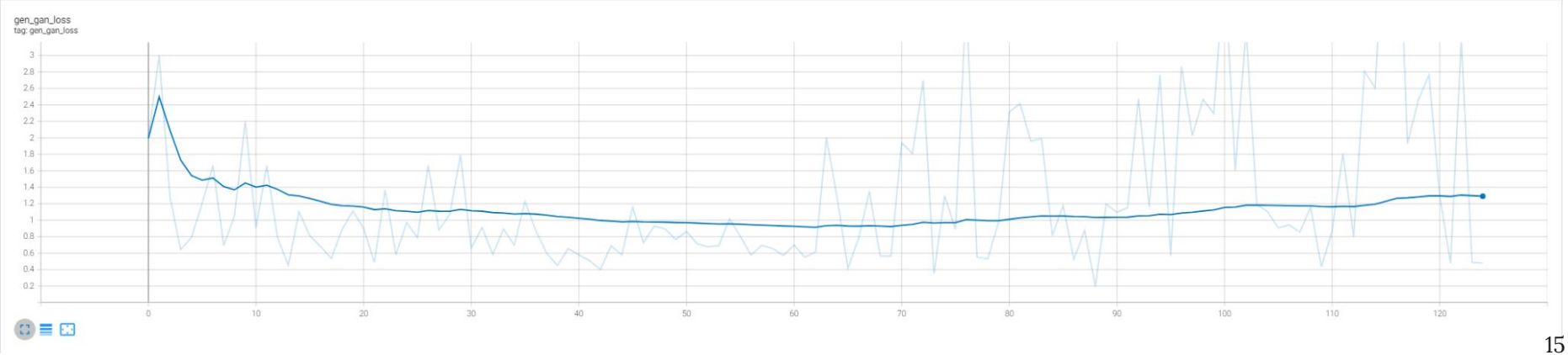
Discriminator



Model One - 125 Image Dataset



gen_gan_loss



Model One - 125 Image Dataset

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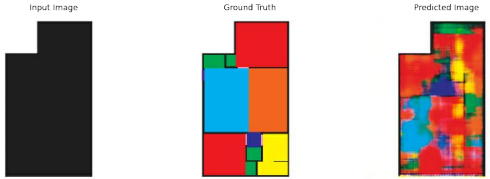
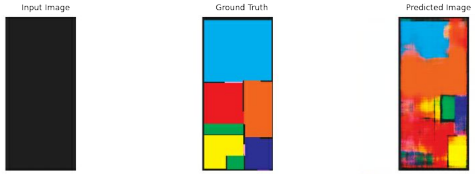
Total	13	8	4	0
Percent	52%	32%	16%	0%

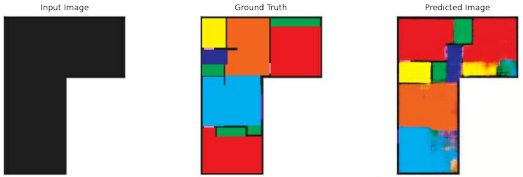
Poor



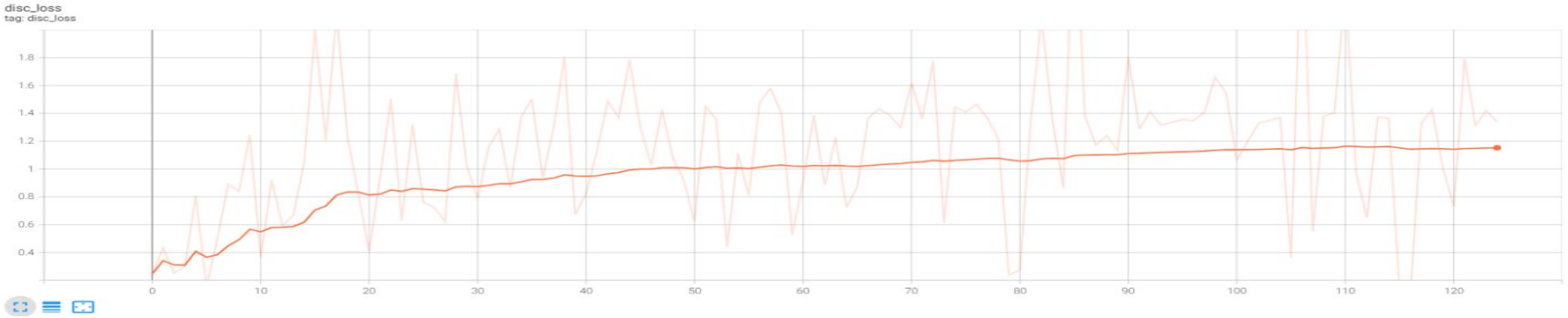
Average

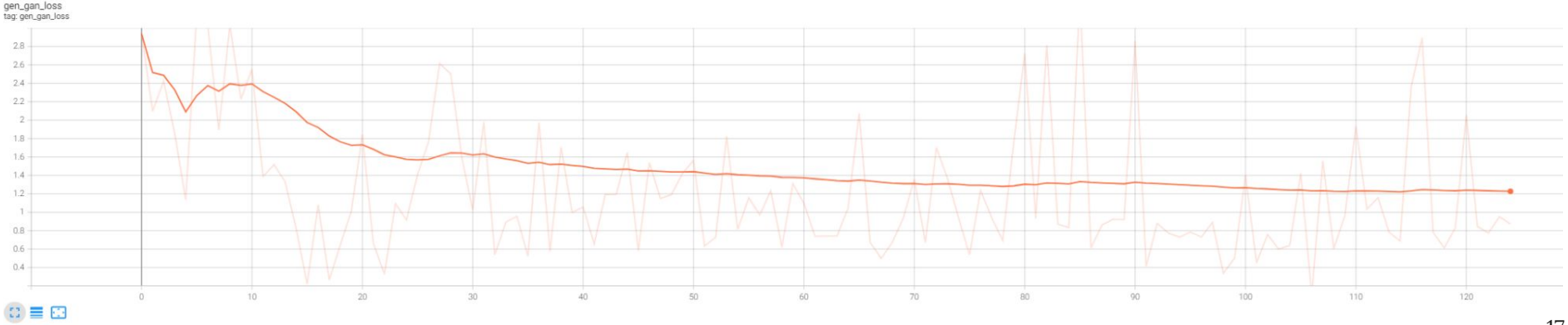


Good



Model Two - 200 Image Dataset

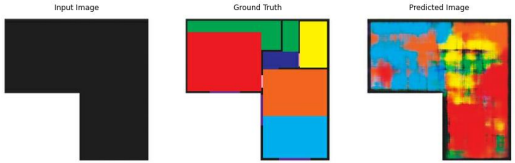




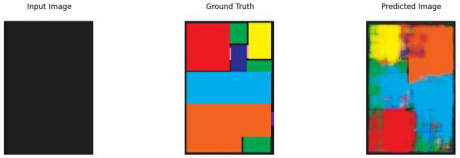
Model Two - 200 Image Dataset

	Poor	Average	Good	Excellent
Total	3	11	18	8
Percent	7.5%	27.5%	45%	20%

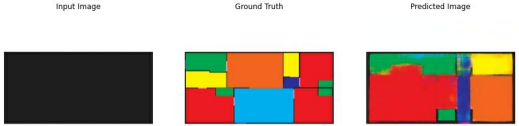
Poor



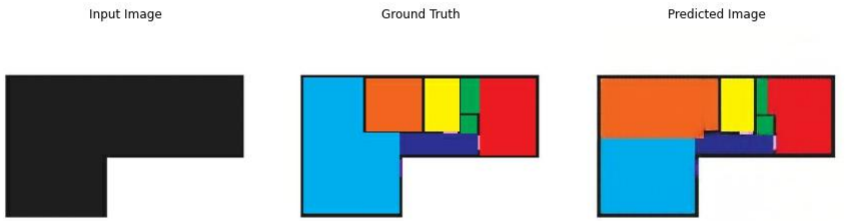
Average

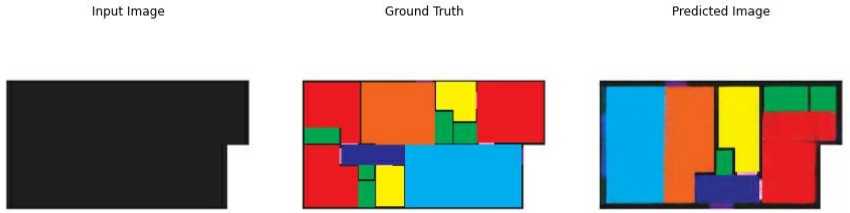


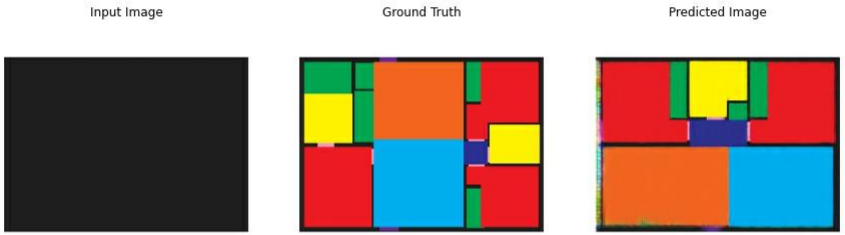
Good

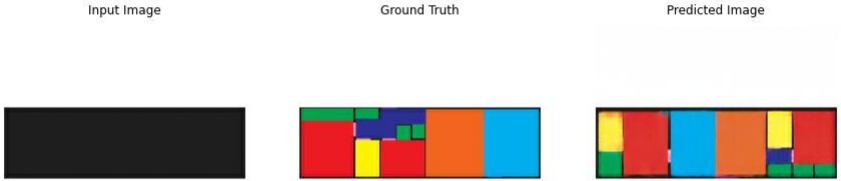


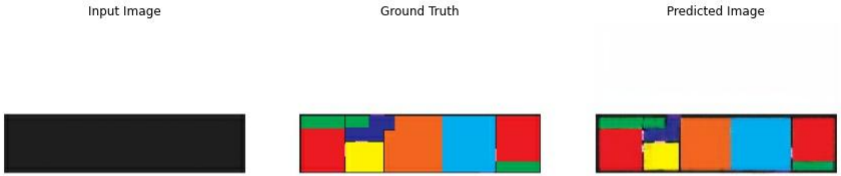
Model Two - Excellent Images

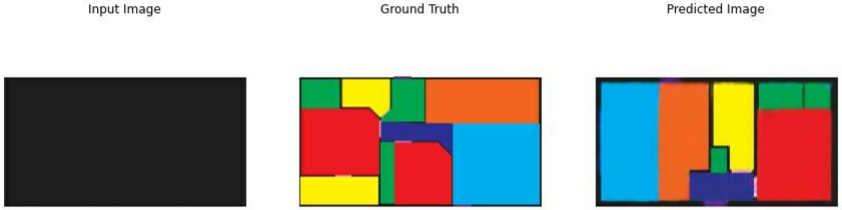




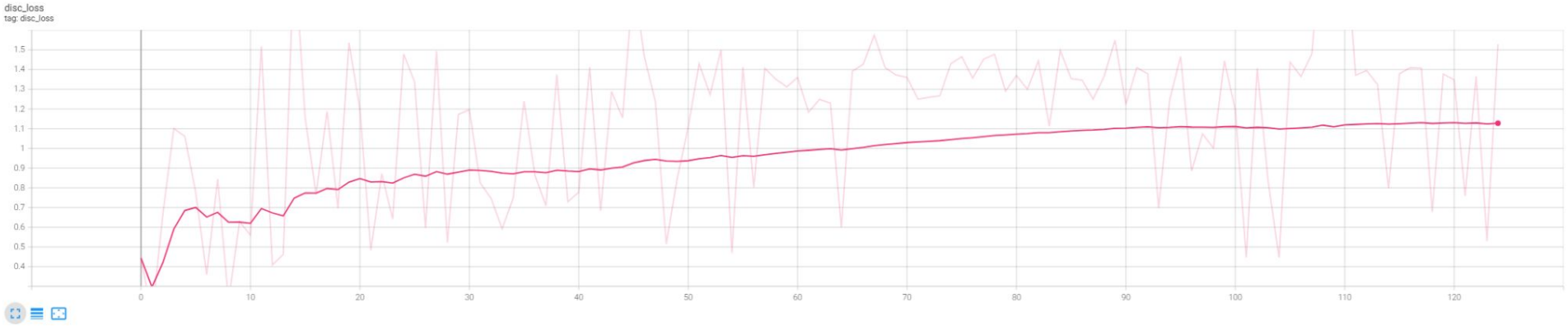


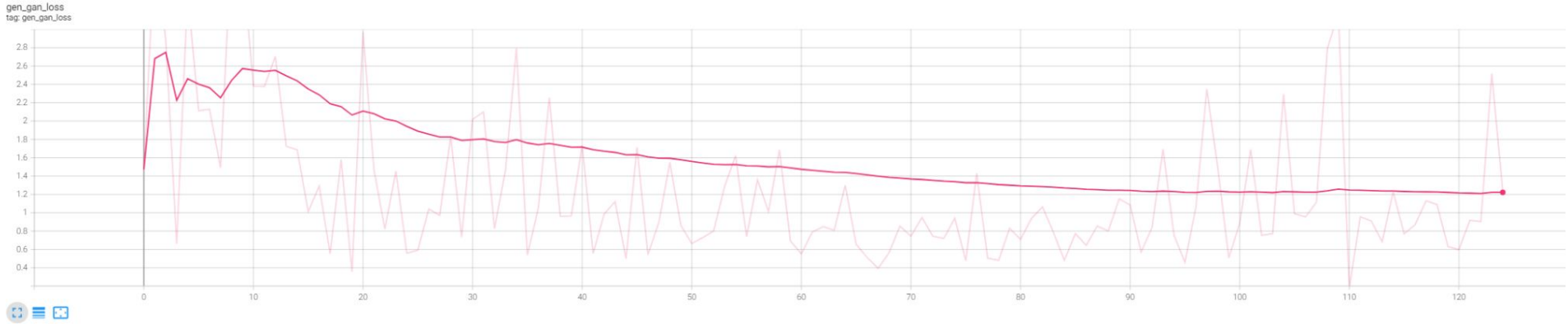






Model Three - 200 Image Extended Dataset

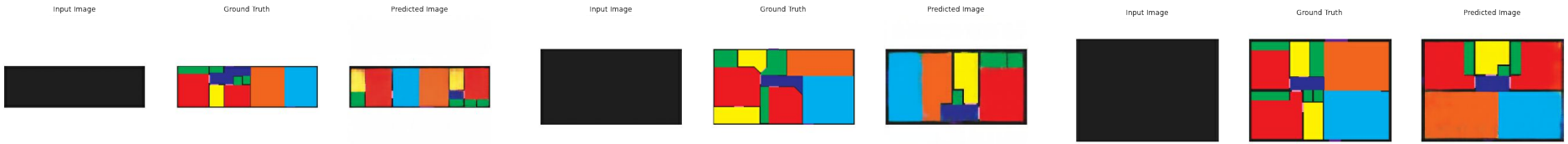




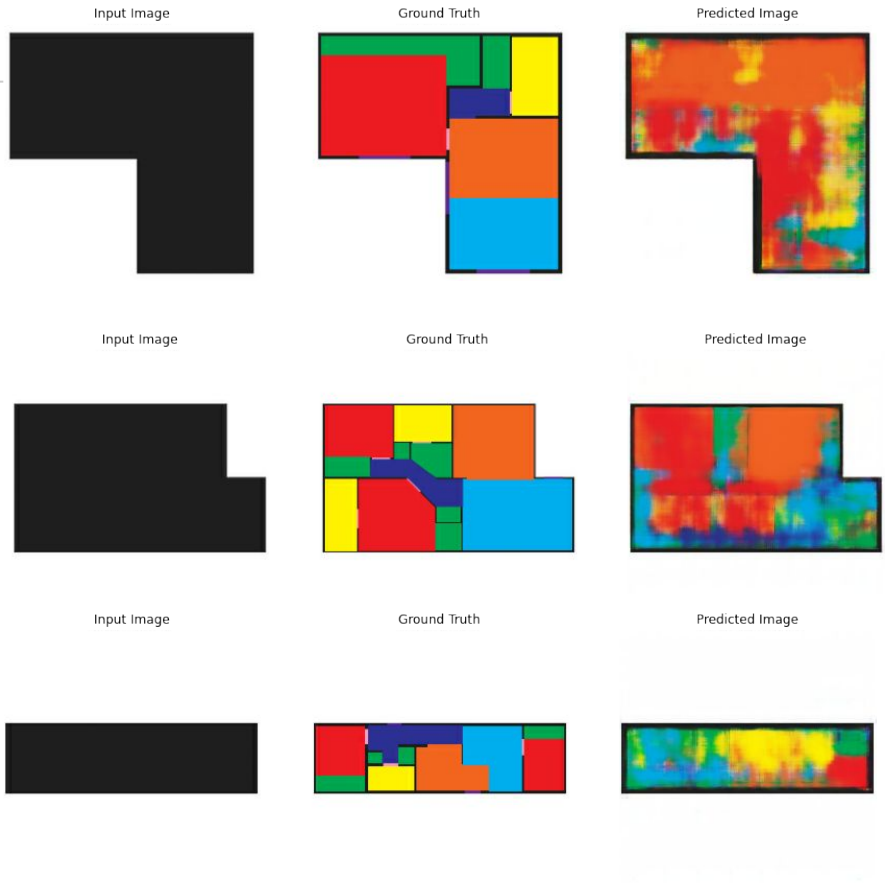
Model Three - 200 Image Extended Dataset

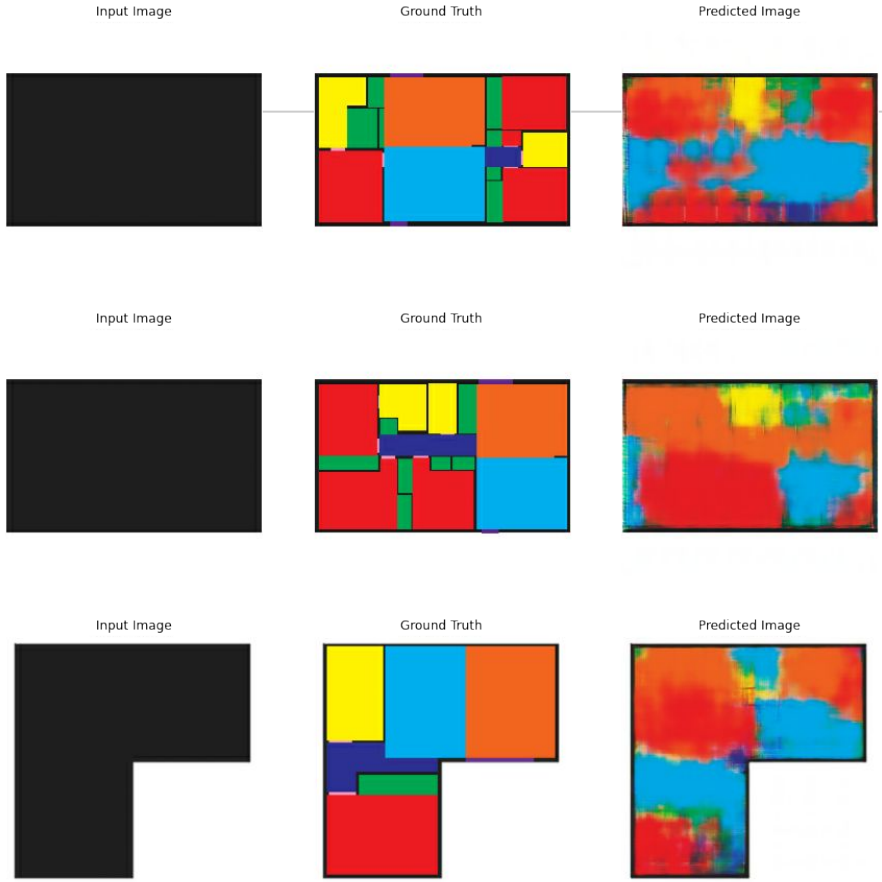
	Poor	Average	Good	Excellent
Total	15	15	2	8
Percent	37.5%	37.5%	5%	20%

Excellent Models

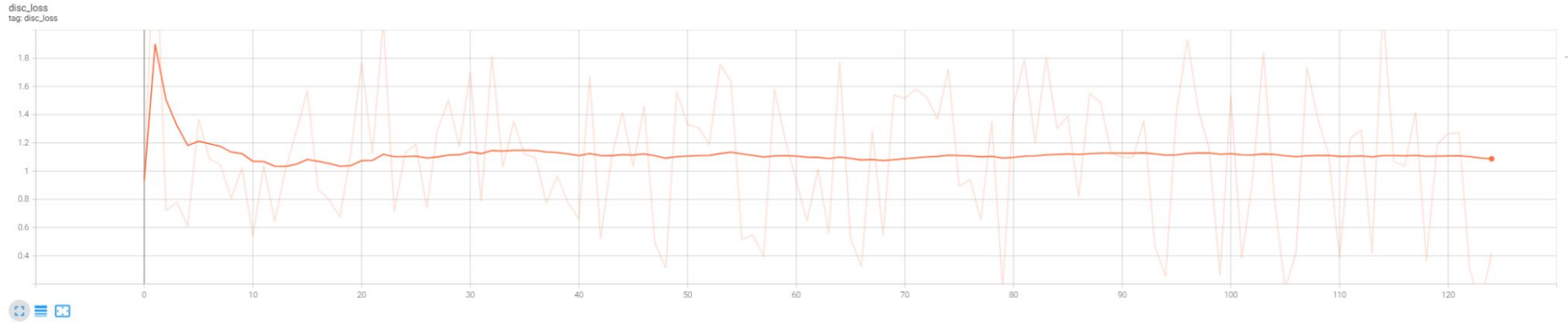


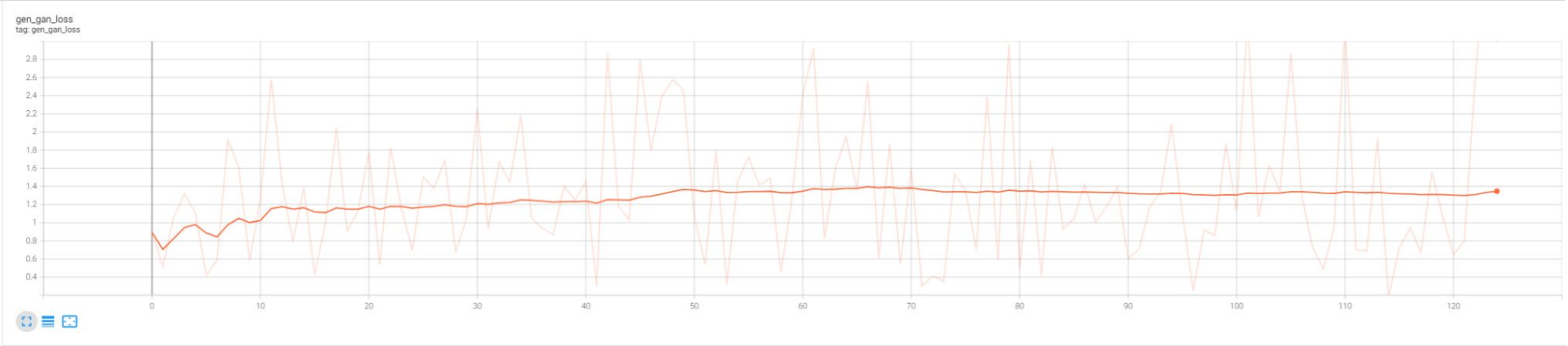
Model Three - Washed Out Images





Model Four - Simple Image Dataset

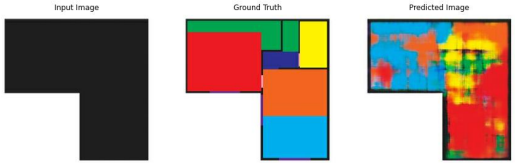




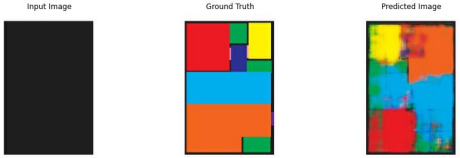
Model Four - Simple Image Dataset

	Poor	Average	Good	Excellent
Total	13	12	5	6
Percent	36.11%	33.33%	13.89%	16.67%

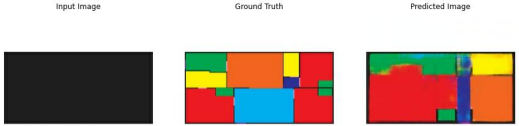
Poor



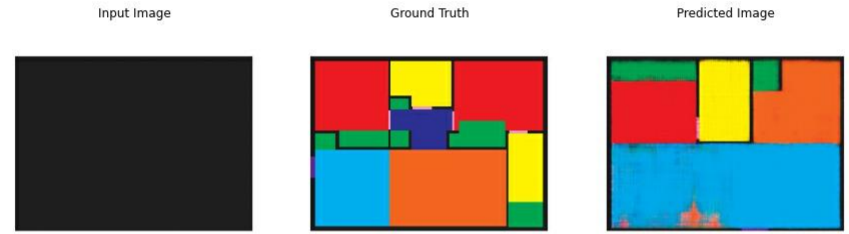
Average

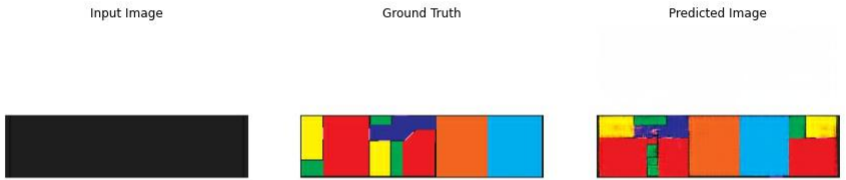


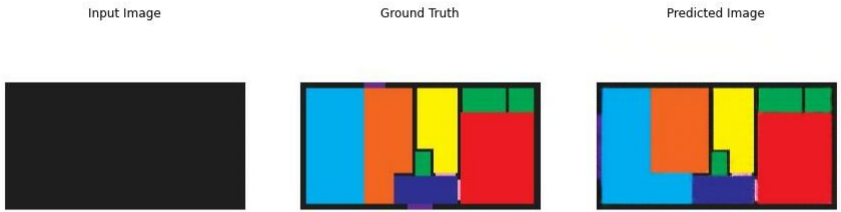
Good

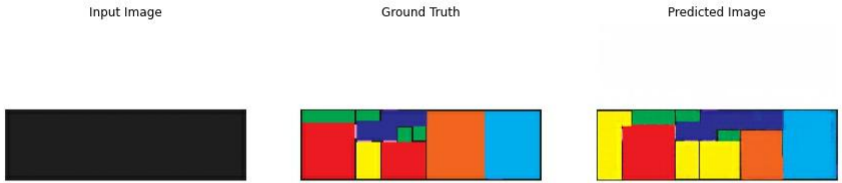


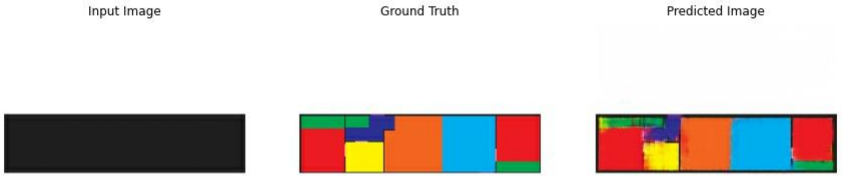
Model Four - Excellent Images

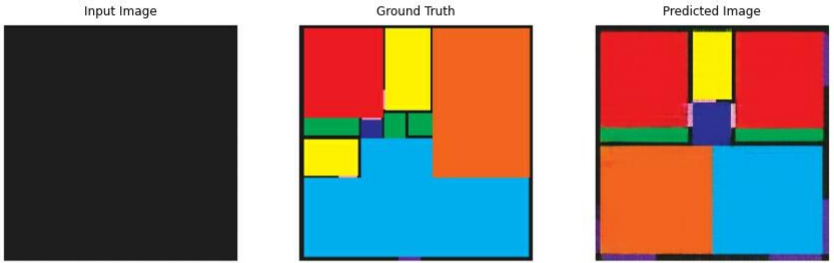








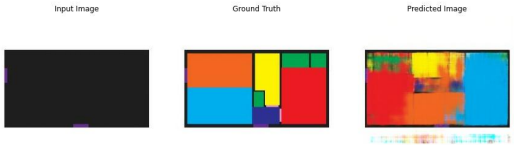




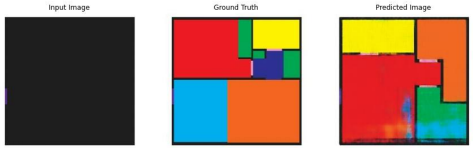
Model Five - Exterior Doors Dataset

	Poor	Average	Good	Excellent
Total	10	19	7	4
Percent	25%	47.5%	17.5%	10%

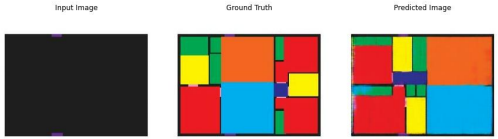
Average



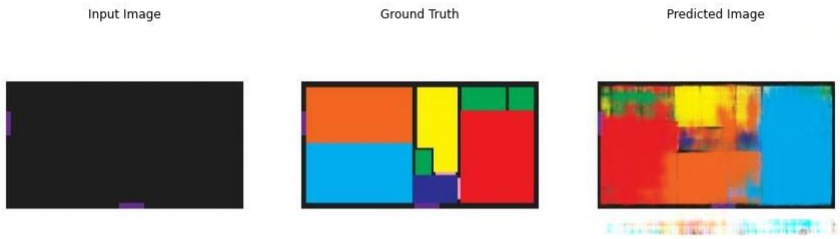
Good

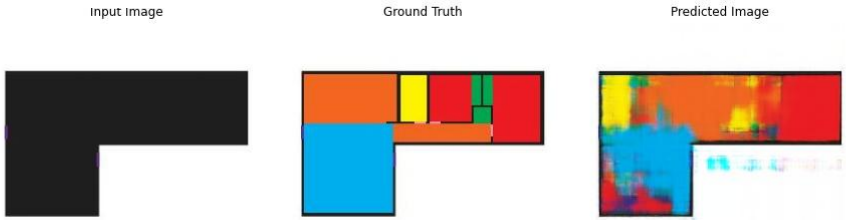


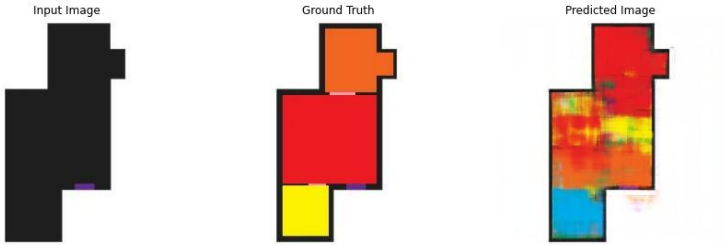
Excellent



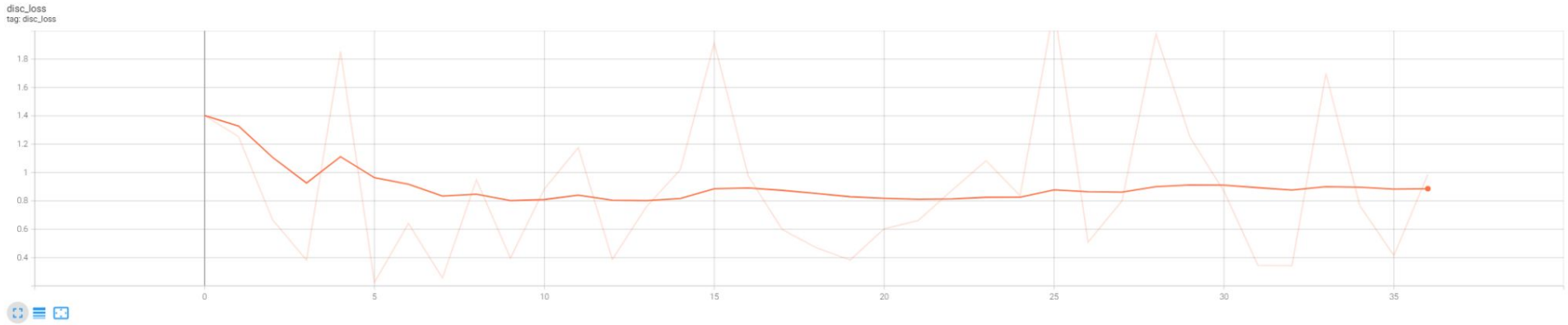
Model Five - Coloring Outside the Lines

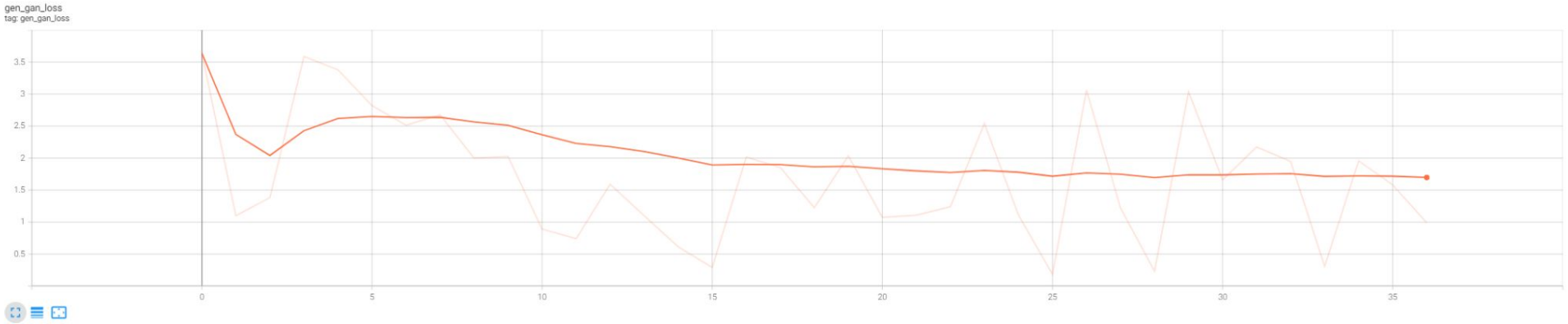






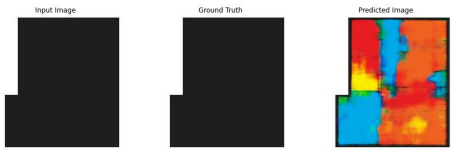
Model Six - Tricky Dataset

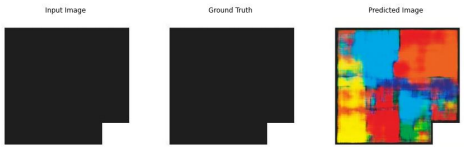




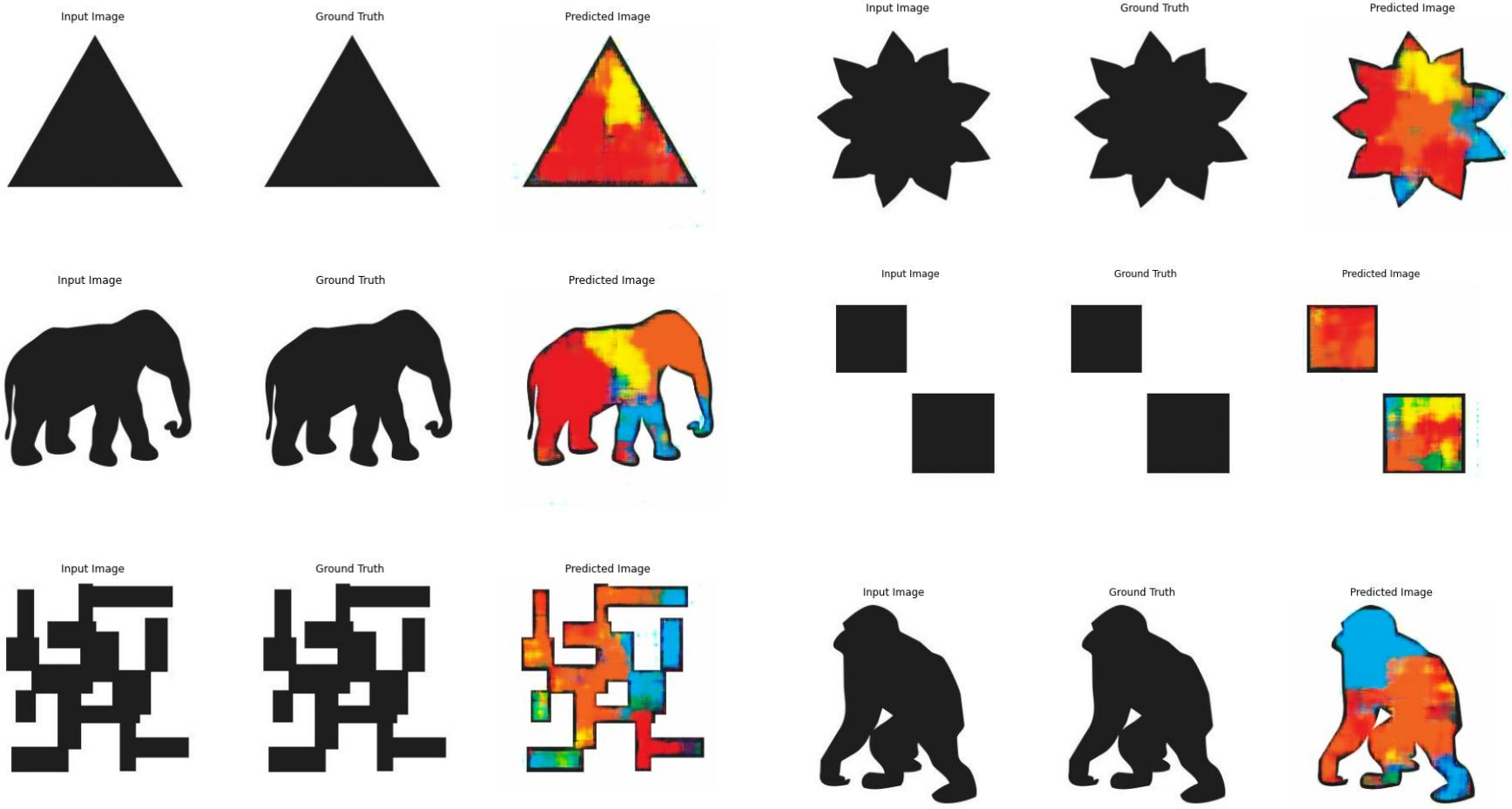
Model Four - Tricky Dataset

	Poor	Average	Good	Excellent
Total	40	0	0	0
Percent	100%	0%	0%	0%





Model 6 - Illegible Images

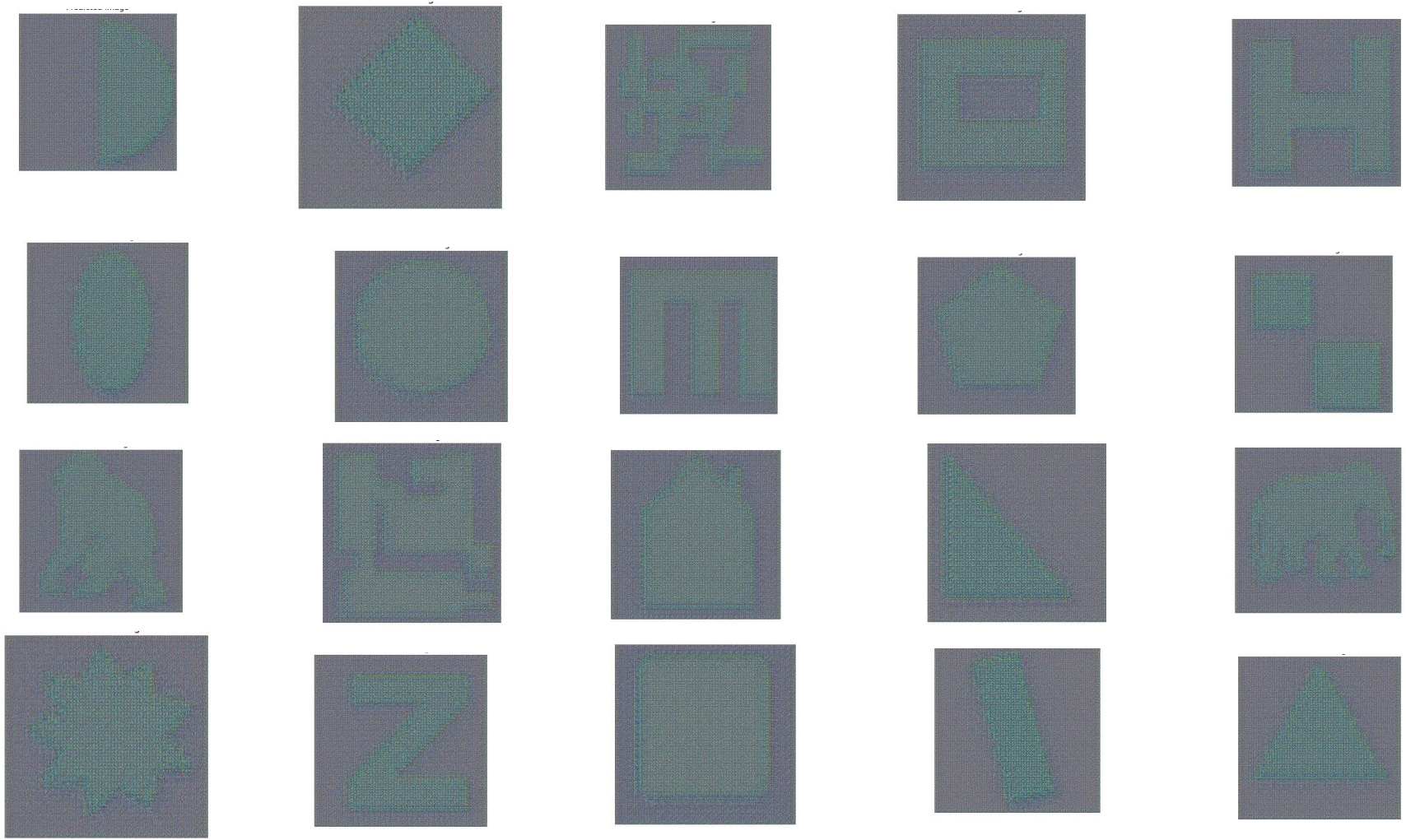


Insights

- Model shows a lot of promise
- Biggest improvements came from adding more data
- No improvements from modifying disc/gen
- Inputs not matching training set drops off greatly
- Model prone to overfitting
- Model does not understand scale

Next Steps

- **Model needs more data**
  - Apartments/cabins
  - Create my own floor plans
- Disc/gen optimization
- Implement square footage as a feature
- Could look at a cycle GAN
- Look into other aspects of ADU modeling
- Create a model with no floor plan discrimination

Credits

- Websites: snapadu.com/snapadu.com/, https://www.delmar.ca.us/815/ADU-Sample-Floor-Plans, https://www.hybridcorehomes.com/adu/, https://proteus.homes/floor-plans/, https://superioradus.com/, https://www.sandiegocounty.gov/content/sdc/pds/bldg/adu_plans.html, https://www.ladbs.org/adu/standard-plan-program/approved-standard-plans, https://adore-homes.com/models/, https://villahomes.com/units/#1-bedroom, https://abodu.com/quickship/, https://www.cotta.ge/, https://adumarin.org/floorplans, https://www.dwell.com/article/adu-floor-plans-06b805c4, https://maxablespace.com/accessory-dwelling-unit-floor-plans/, https://www.modernaduplans.com/adu-plans
- pix2pix Tutorial: https://www.tensorflow.org/tutorials/generative/pix2pix