The Intersection between Fashion & Machine Learning

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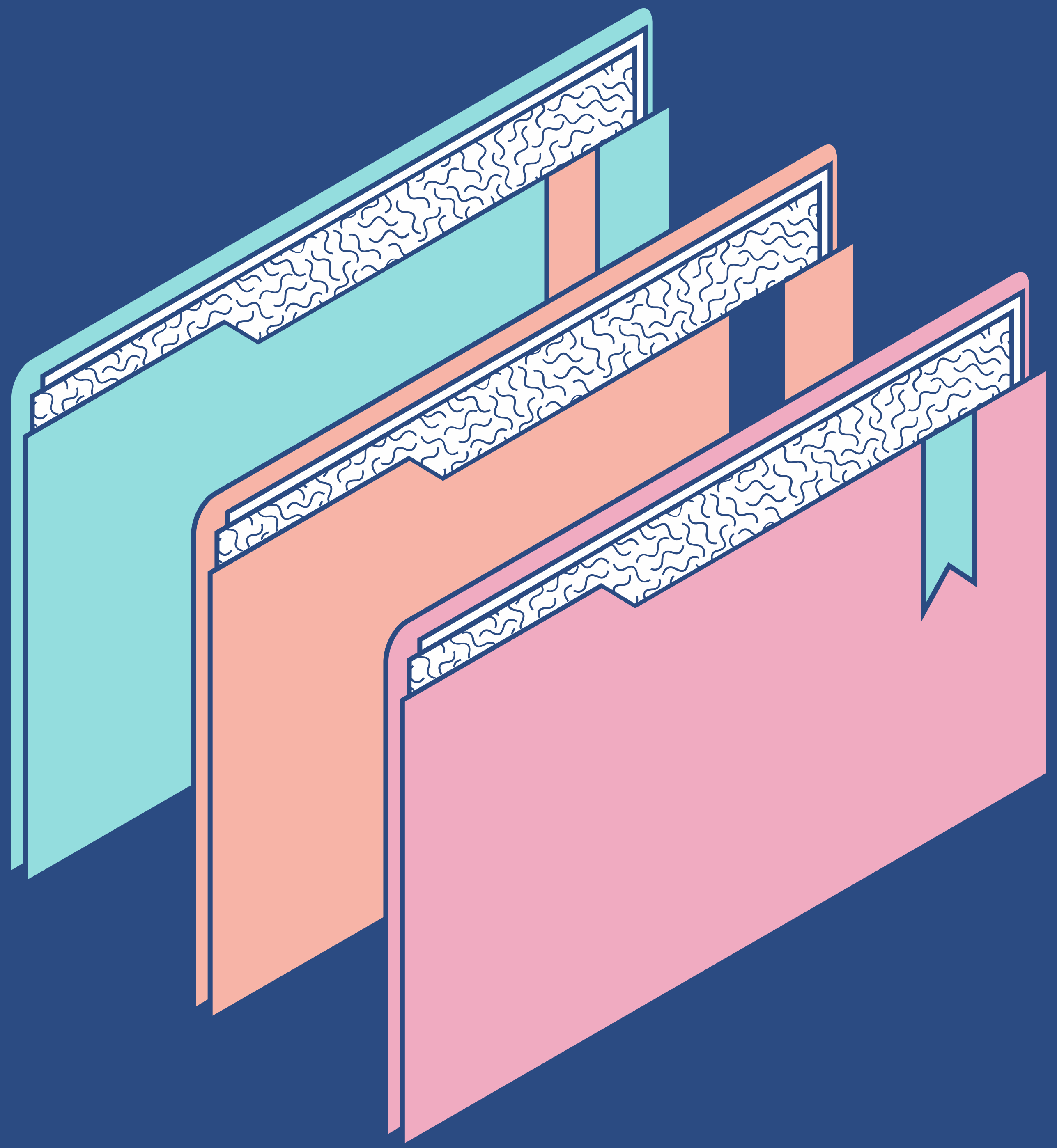
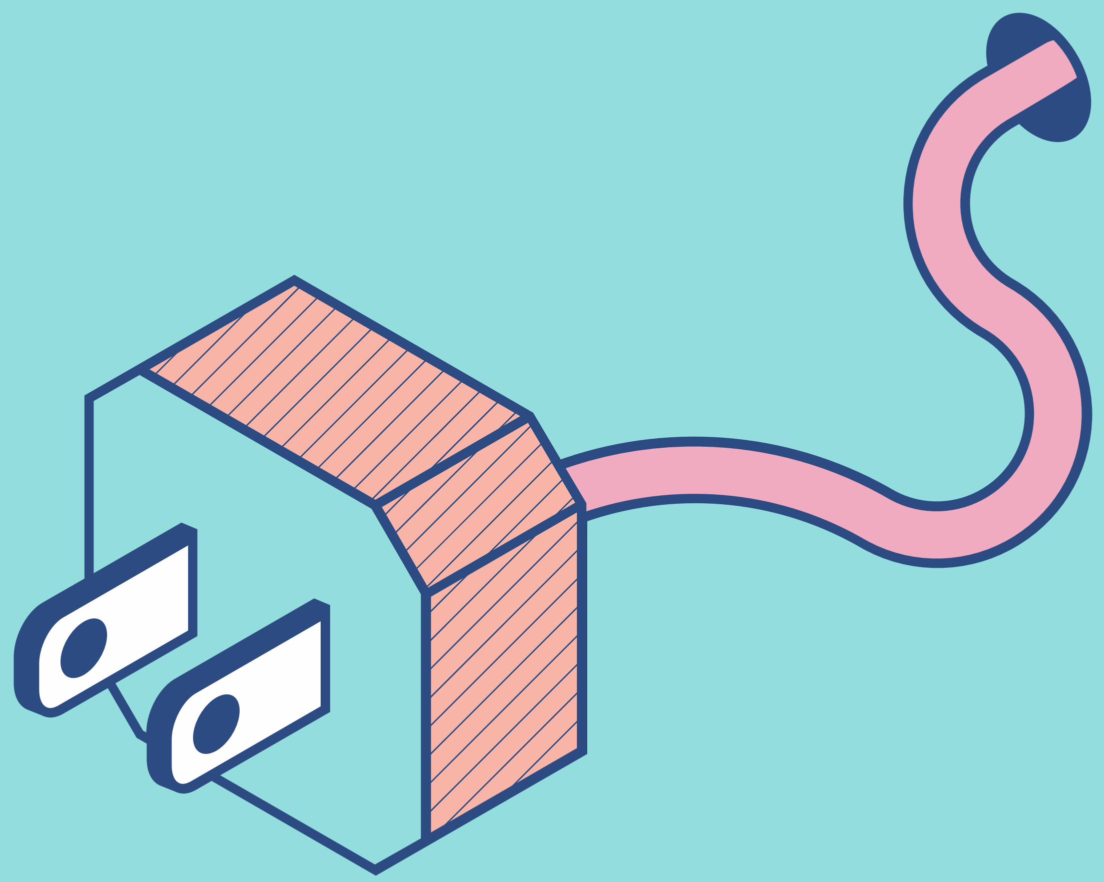
Motivation/Problem Description

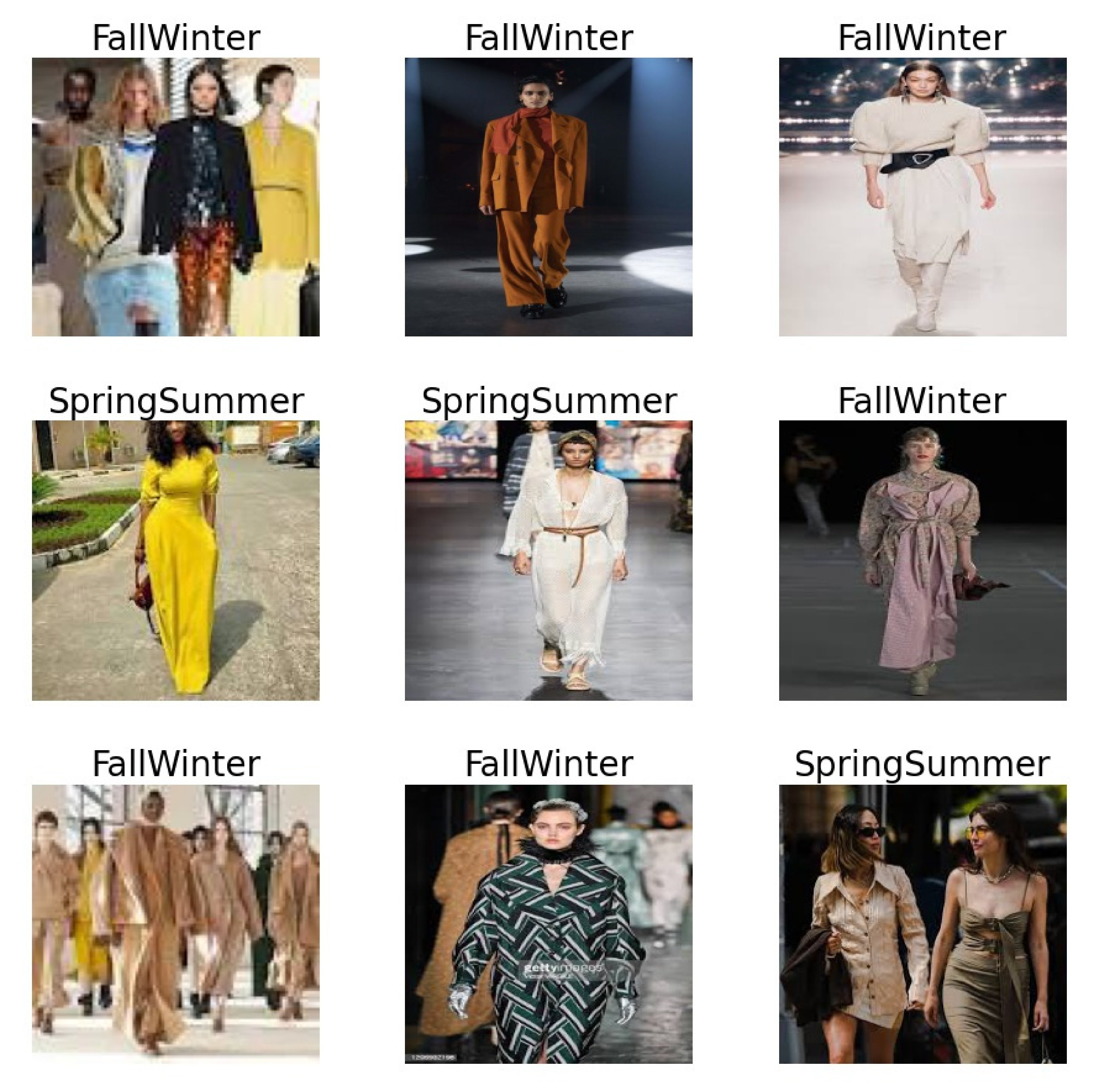


- To mend my passion for machine learning and fashion into a real world use case
- Creating a deep learning model to recognize/classify seasonal fashion trends
- How this can be translated into business tool

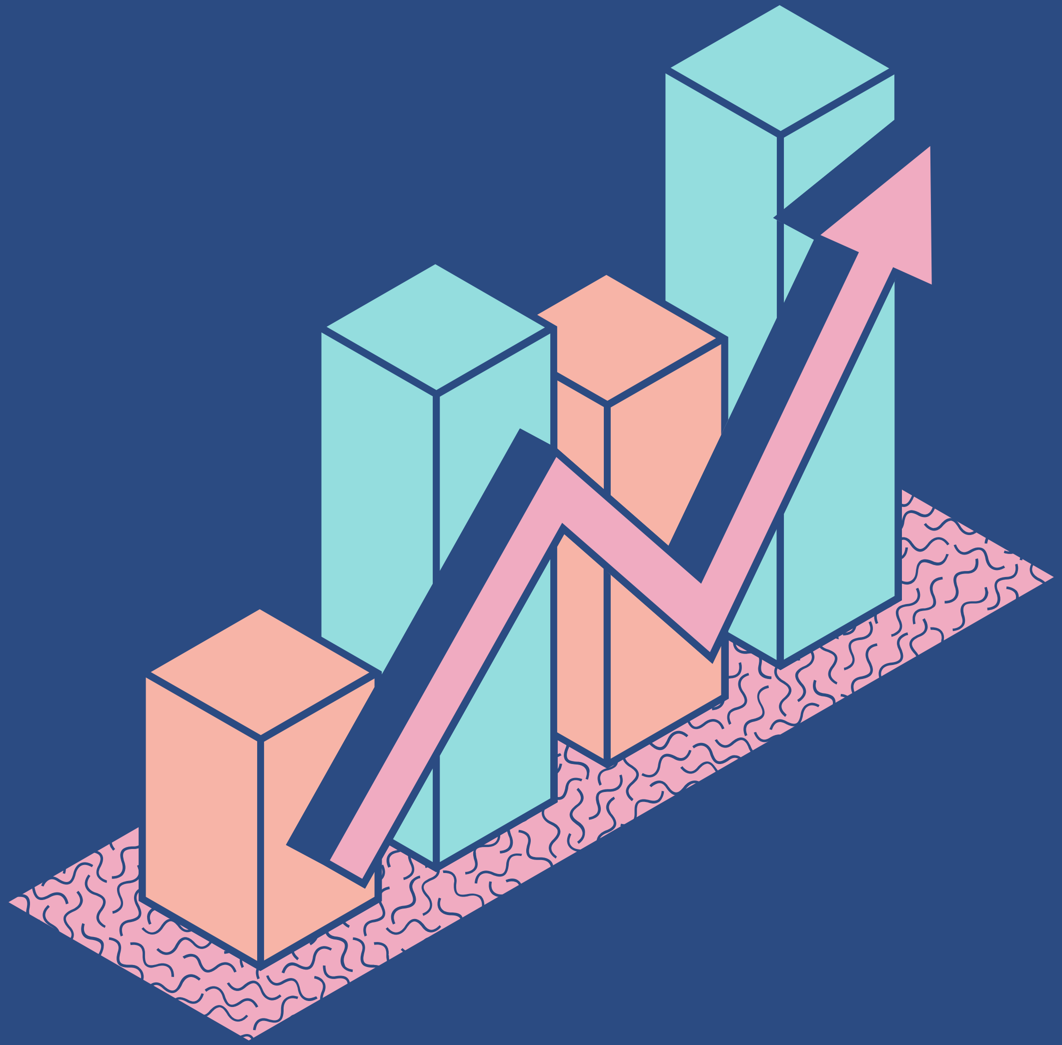
How do we approach this problem?

1. Narrow down the target area of fashion to focus on
   a. High end , small businesses, purses, clothing, etc.
2. Gather necessary technology to carry out the research.
   a. Deep learning, Neural Network w/ PyTorch, Transfer Learning





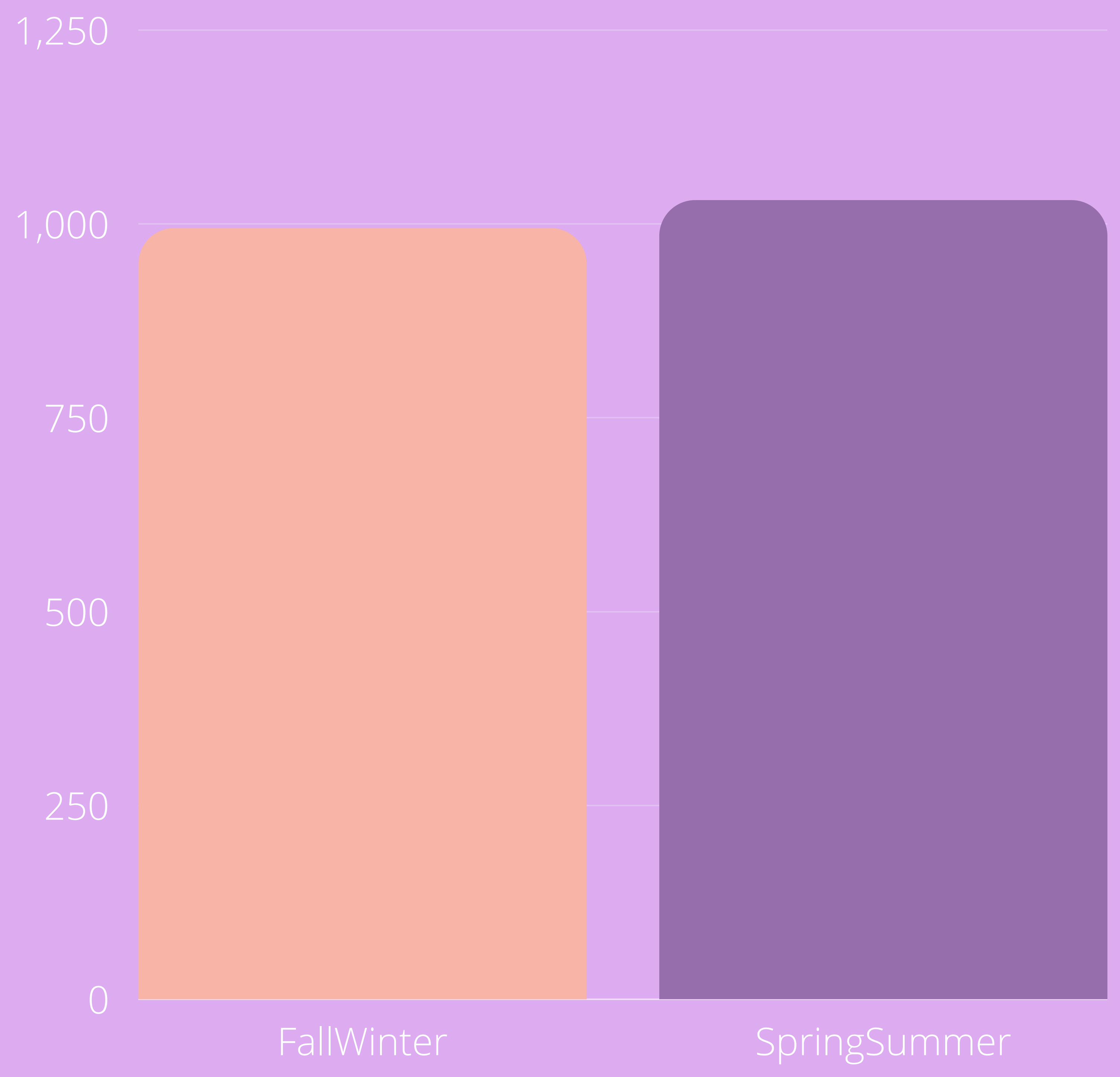
Random Sample pictures



Class distribution

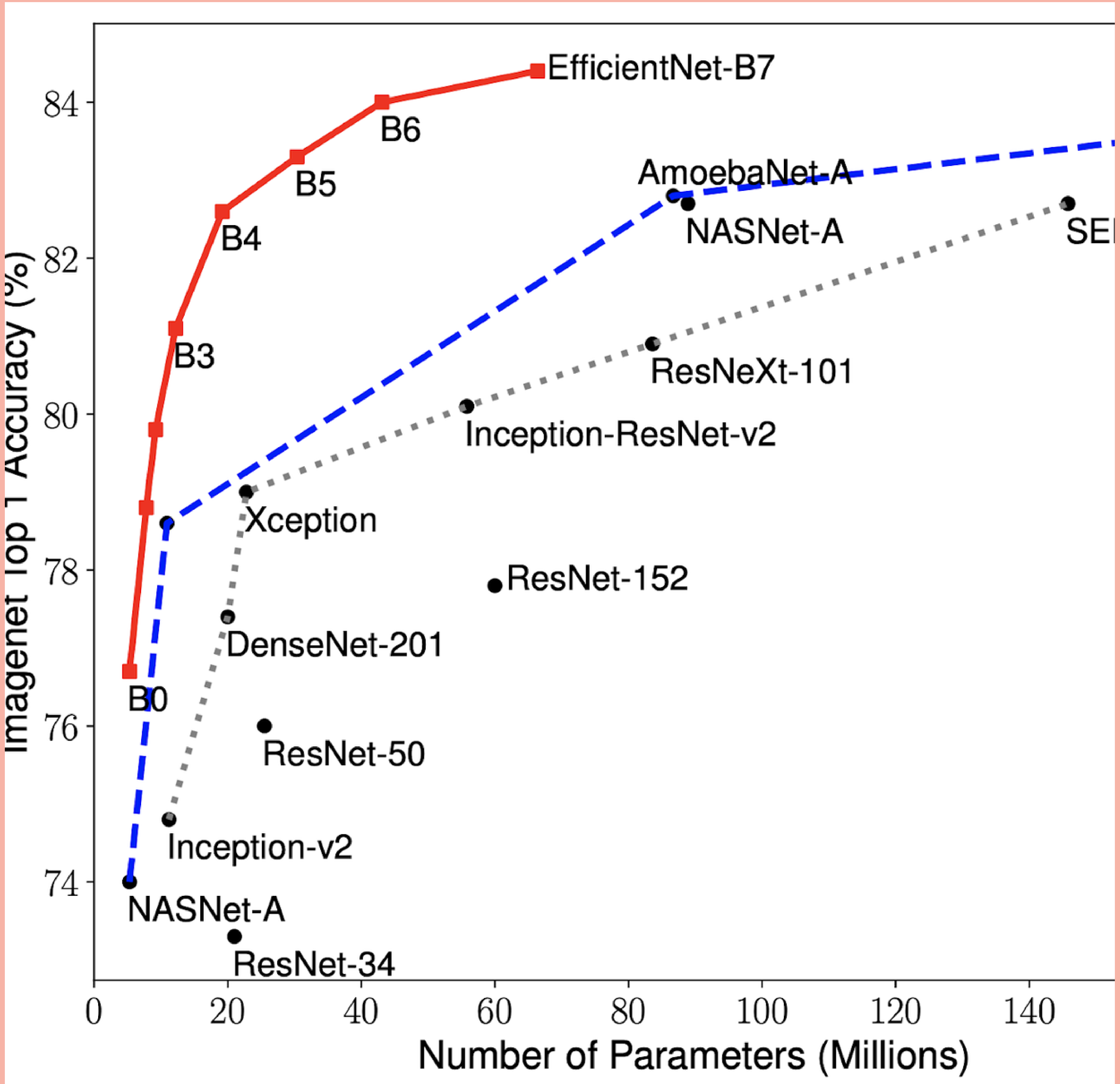
BRANDS SUCH AS : CHANEL, DIESEL, PRADA, ALYX

- About 1000 pictures for each class
- More samples give a learning algorithm more opportunity to understand the underlying mapping of inputs to outputs, and, in turn, a better performing model.

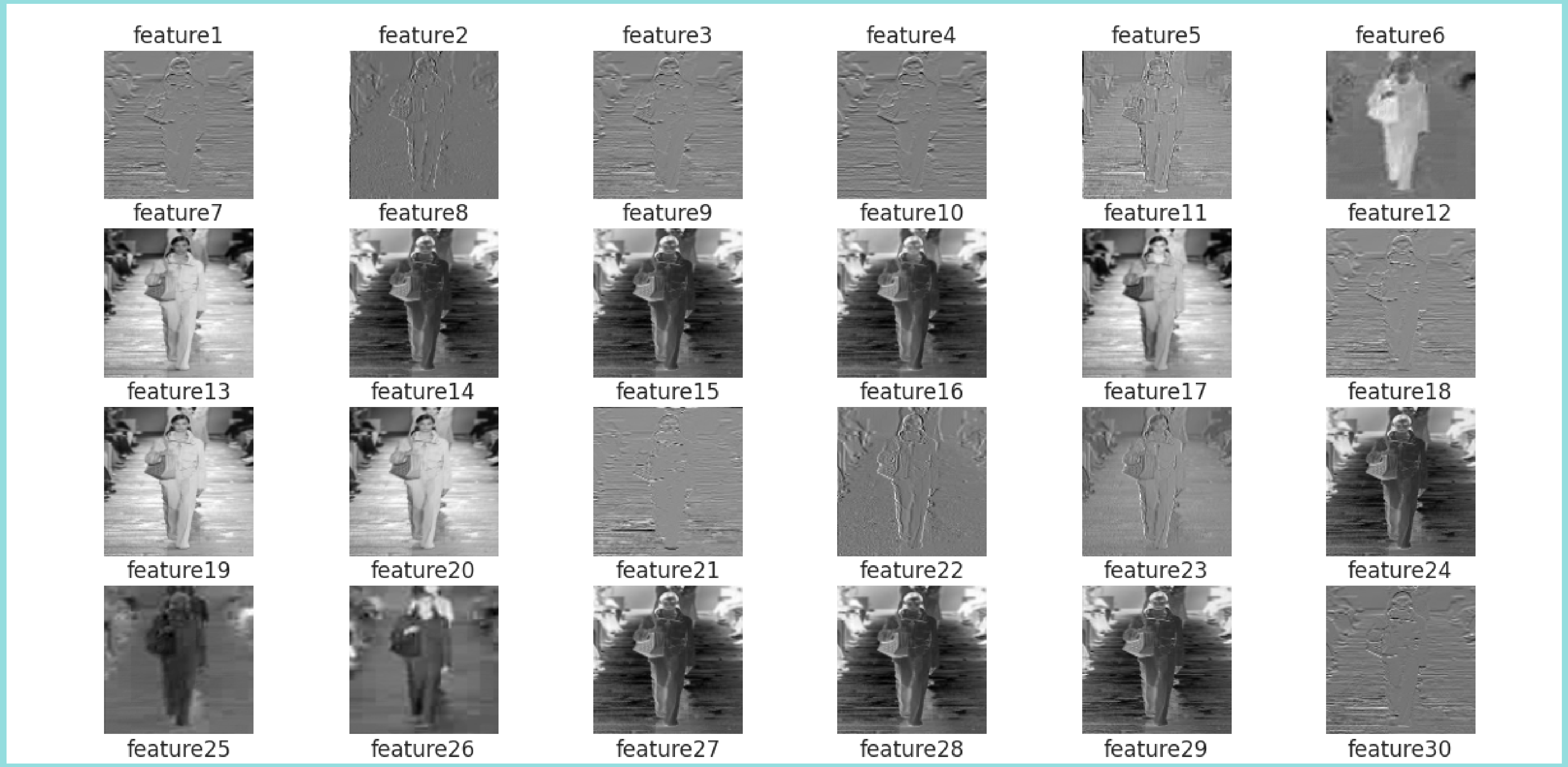


Training the Deep Learning Model

Transfer Learning w/ PyTorch



How the Algorithm Works



How Machines(!) learn


```
==========================================================================================
Layer (type:depth-idx)                             Output Shape              Param #
==========================================================================================
EfficientNet                                       --                        --
├─Conv2d: 1-1                                      [8, 32, 112, 112]         864
├─BatchNorm2d: 1-2                                 [8, 32, 112, 112]         64
├─SiLU: 1-3                                        [8, 32, 112, 112]         --
├─Sequential: 1-4                                  [8, 320, 7, 7]            --
│    └─Sequential: 2-1                             [8, 16, 112, 112]         --
│    │    └─DepthwiseSeparableConv: 3-1            [8, 16, 112, 112]         1,448
│    └─Sequential: 2-2                             [8, 24, 56, 56]           --
│    │    └─InvertedResidual: 3-2                  [8, 24, 56, 56]           6,004
│    │    └─InvertedResidual: 3-3                  [8, 24, 56, 56]           10,710
│    └─Sequential: 2-3                             [8, 40, 28, 28]           --
│    │    └─InvertedResidual: 3-4                  [8, 40, 28, 28]           15,350
│    │    └─InvertedResidual: 3-5                  [8, 40, 28, 28]           31,290
│    └─Sequential: 2-4                             [8, 80, 14, 14]           --
│    │    └─InvertedResidual: 3-6                  [8, 80, 14, 14]           37,130
│    │    └─InvertedResidual: 3-7                  [8, 80, 14, 14]           102,900
│    │    └─InvertedResidual: 3-8                  [8, 80, 14, 14]           102,900
│    └─Sequential: 2-5                             [8, 112, 14, 14]          --
│    │    └─InvertedResidual: 3-9                  [8, 112, 14, 14]          126,004
│    │    └─InvertedResidual: 3-10                 [8, 112, 14, 14]          208,572
│    │    └─InvertedResidual: 3-11                 [8, 112, 14, 14]          208,572
│    └─Sequential: 2-6                             [8, 192, 7, 7]            --
│    │    └─InvertedResidual: 3-12                 [8, 192, 7, 7]            262,492
│    │    └─InvertedResidual: 3-13                 [8, 192, 7, 7]            587,952
│    │    └─InvertedResidual: 3-14                 [8, 192, 7, 7]            587,952
│    │    └─InvertedResidual: 3-15                 [8, 192, 7, 7]            587,952
│    └─Sequential: 2-7                             [8, 320, 7, 7]            --
│    │    └─InvertedResidual: 3-16                 [8, 320, 7, 7]            717,232
├─Conv2d: 1-5                                      [8, 1280, 7, 7]           409,600
├─BatchNorm2d: 1-6                                 [8, 1280, 7, 7]           2,560
├─SiLU: 1-7                                        [8, 1280, 7, 7]           --
├─SelectAdaptivePool2d: 1-8                        [8, 1280]                 --
│    └─AdaptiveAvgPool2d: 2-8                      [8, 1280, 1, 1]           --
│    └─Flatten: 2-9                                [8, 1280]                 --
├─Linear: 1-9                                      [8, 1000]                 1,281,000
==========================================================================================
Total params: 5,288,548
Trainable params: 5,288,548
Non-trainable params: 0
Total mult-adds (G): 3.09
==========================================================================================
Input size (MB): 4.82
Forward/backward pass size (MB): 863.09
Params size (MB): 21.15
Estimated Total Size (MB): 889.06
------------------------------------------------------------------------------------------
```

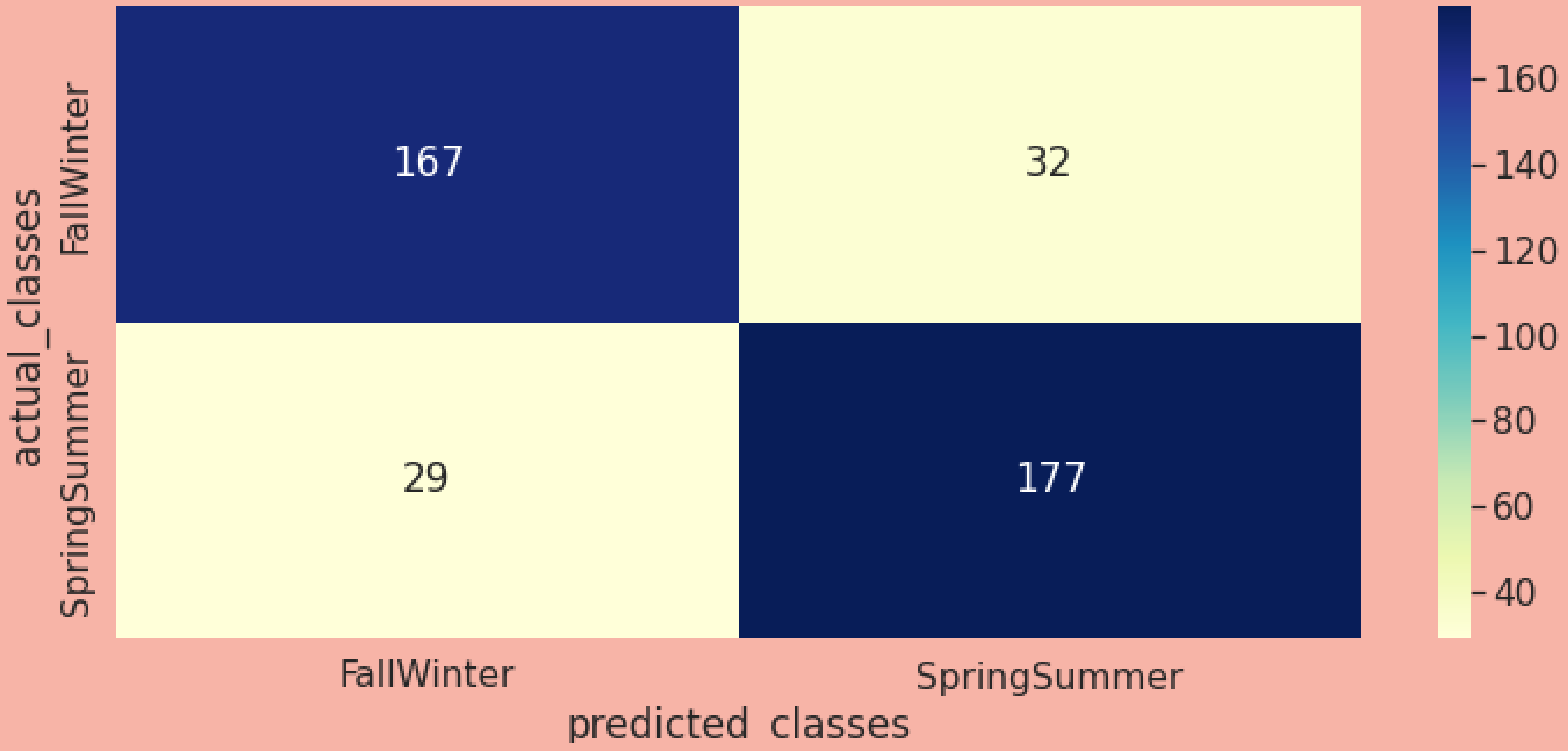
2

Training Efficient Net w/ Optuna

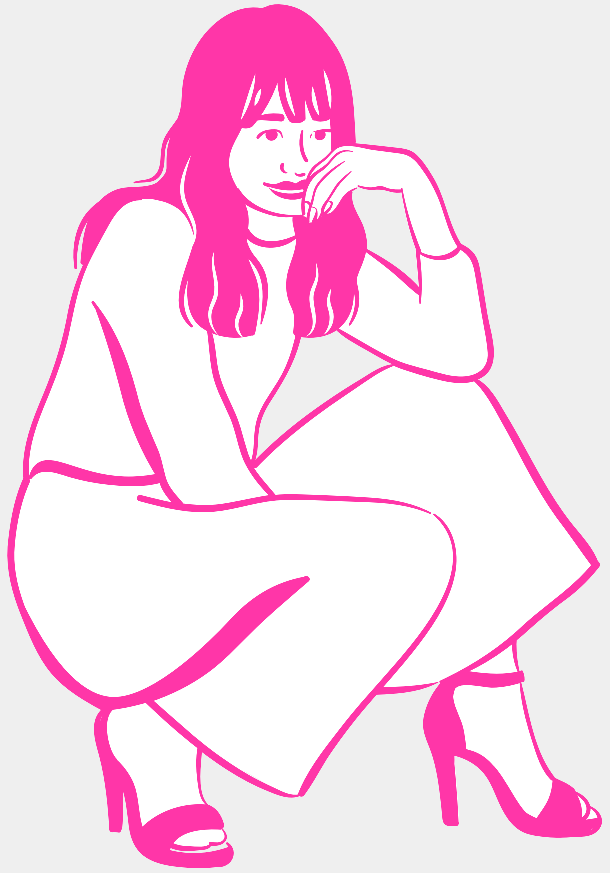
A	B	C	D	E	F	G	H
number	value	duration	params_freeze	params_lr	params_train_batch_size	params_weight_decay	state
1	0.82	3.57	False	0.00061	31	0.00095	COMPLETE
2	0.81	3.63	False	0.00069	22	0.00043	COMPLETE
3	0.81	3.55	False	0.00061	29	0.00096	COMPLETE
6	0.81	3.57	False	0.00031	26	0.00090	COMPLETE
9	0.81	3.65	False	0.00028	25	0.00028	COMPLETE
8	0.80	3.6	False	0.00033	23	0.00032	COMPLETE
4	0.80	3.52	False	0.00066	32	0.00021	COMPLETE
0	0.78	3.78	False	0.00080	18	0.00051	COMPLETE
5	0.78	3.73	False	0.00078	19	0.00031	COMPLETE
10	0.78	3.53	False	0.00095	32	0.00071	COMPLETE
11	0.78	3.67	False	0.00048	21	0.00053	COMPLETE
7	0.89	3.7	False	0.00066	18	0.00083	PRUNED

Results: Confusion Matrix

- OVERALL ACCURACY IS 85 %!



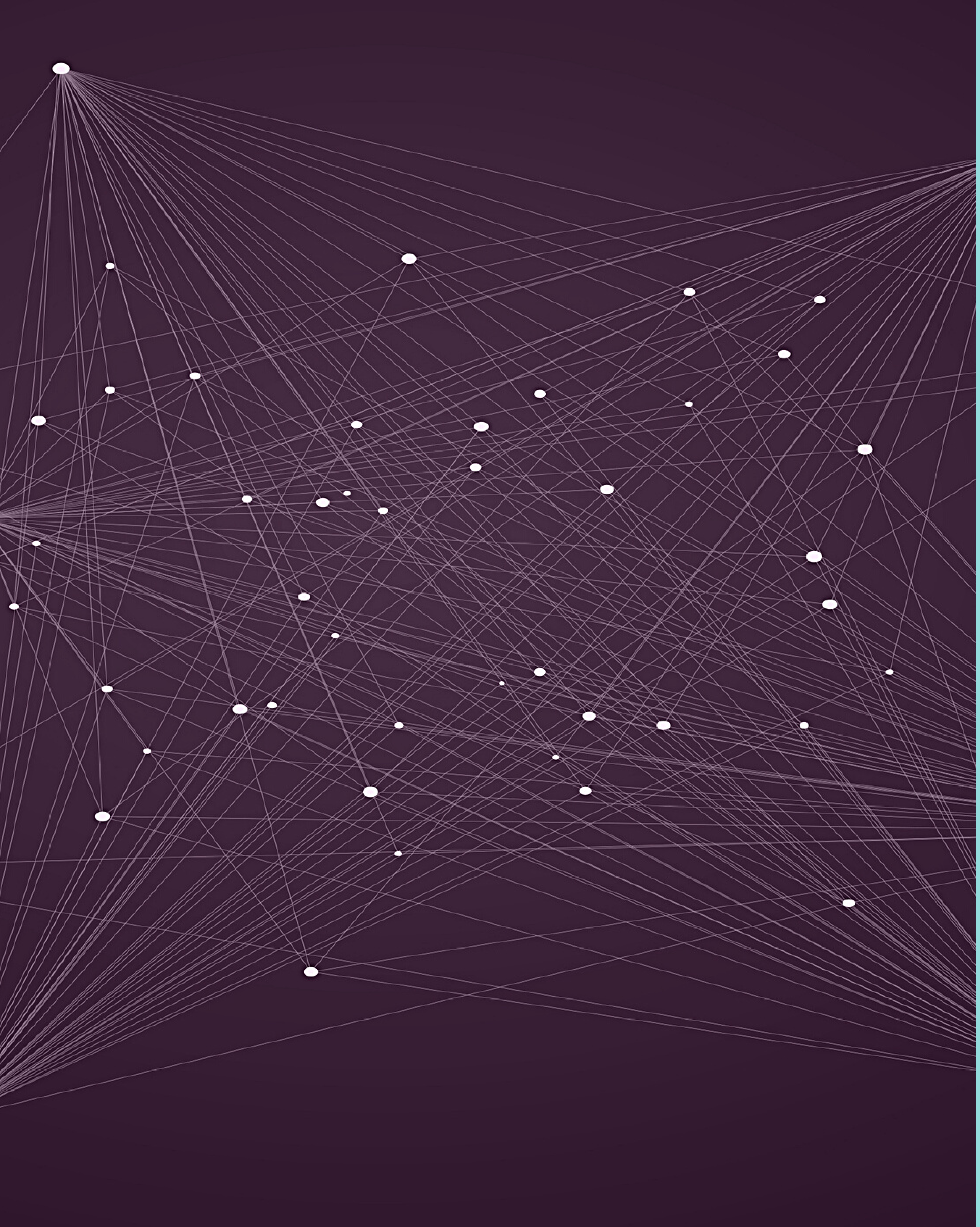
Correct Predictions



Misinterpreted Predictions

How this can be used as a business tool

Trend forecasting - The process of researching and formulating predictions on consumers future buying habits and/or producers future product .



Roadblocks faced

TOO SIMILAR IMAGES CAN LEAD TO SKEWED RESULTS

- Started off with Fall , Winter, Spring , Summer
- Creating a color pallet for each season to help it become more precise
- Overall accuracy is around 50% since spring-summer and fall-winter classes look pretty similar

Thank You for listening!