# Apparel & Footwear Prediction

Team: A4

Names: Becky Wang, Chia-Chien Chang,

Xinying Wu, Vy Nguyen, Yunling Li

-ootwear



Apparel



## **TABLE OF CONTENTS**



Introduction



Performance



**Dataset** 



**Base Model** 



**Other Models** 



**Best Model** 



**Managerial Implications** 



01

# Introduction



## Introduction

#### Outcome variable: product category

• Binary : O = Apparel; 1 = Footwear

#### Business Application: automated product categorization for e-commerce

- Reduce manual tagging and errors in large product catalogs
- Improve search and filtering, making it easier for shoppers to find products
- Enhance recommendations and visual search, leading to better user experiences
- Detect miscategorized listings, keeping platforms well-organized



02

# Performance



#### Performance

#### Metric(s)

We primarily use "accuracy" as our evaluation metric:

- The classes are reasonably balanced (Apparel = 46%, Footwear = 54%), so accuracy is meaningful
- It's an intuitive metric for business users to understand and aligns with the goal of **correct classification**

#### **Human Performance**

Approximate human performance for classifying Apparel vs. Footwear is close to 100%, as the distinction is visually obvious to humans.



# 03

# Dataset



#### **Dataset Overview**

Total image



Total images: 2906

Apparel (label 0)



Apparel: 1326

**Ratio: 46%** 

Footwear(label 1)



Apparel: 1580

**Ratio:** 54%

## Image Sizes & Examples

Image sizes vary, but common dimensions are

(1800, 2400) and (1080, 1440)

		1 (0) 5		
	Example I	mages: Apparel (0) vs. Foo	otwear (1)	
Label 0	Label 0	Label 0	Label 0	Label 0
1			AGE A	INT ATT ITU GENT DE
Label 1	Label 1	Label 1	Label 1	Label 1
	Contract of the Contract of th		The state of the s	

# **Data Split**







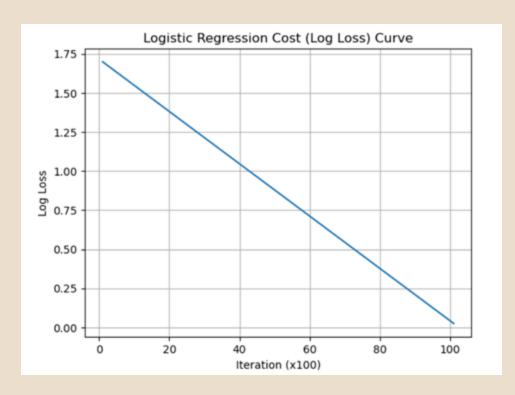


The dataset was split using stratified sampling to preserve class balance, following a 60%/20%/20% ratio.



04 Base Model

# Logistic Regression (no hidden layers)

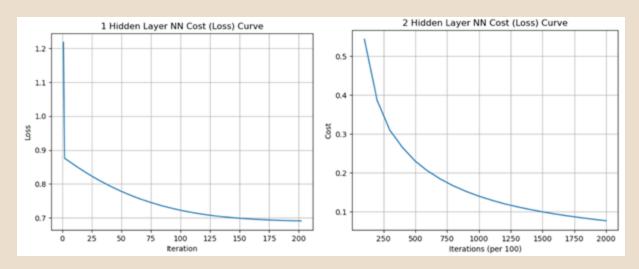


Learning rate: 0.001

Training Accuracy: 99.7% Validation Accuracy: 99.3%

- No signs of overfitting or underfitting
- Loss is smoothly decreasing, suggesting well-tuned learning rate and parameters

## **Neural Network**



- Performance increased with a bigger neural network
- Loss graph of 2 hidden layers NN shows a more expressive model that captures patterns more effectively
- No signs of overfitting or underfitting

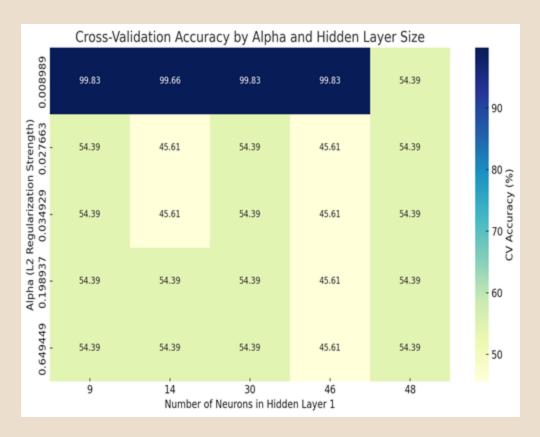
	Training Accuracy	Cross-validation Accuracy
1 hidden layer of 4 units	54.3%	54.3%
2 hidden layers (7 units - 4 units)	99.5%	100%



# 05 Other Models



## 5.1 Performance of 5 different learning rates



Best learning rate: 0.0089
Best hidden unit for this learning rate: 30

Training Accuracy: 99.6% Cross-validation Accuracy: 99.8%

- No clear improvement
- Cross-validation Accuracy dropped but closer to the training accuracy
- No signs of overfitting or underfitting



## 5.1 Performance of 5 different learning rates

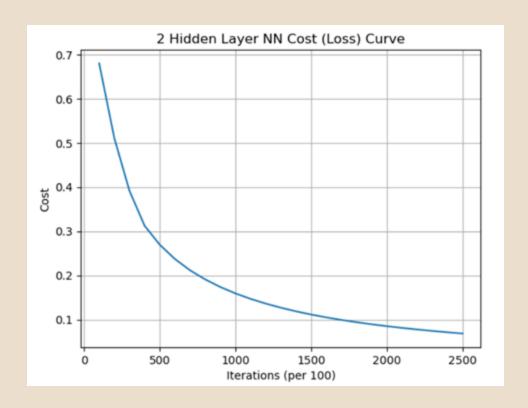
#### New model architecture

Learning rate = 0.0089

Hidden layer 1: 30, ReLU activation

Hidden layer 2: 4, ReLU activation

- Curve is smooth and progressively flattens out
- Loss is consistently decreasing





# 5.2 Performance of different optimization algorithms

Best algorithm: SGD with Momentum = 0.5

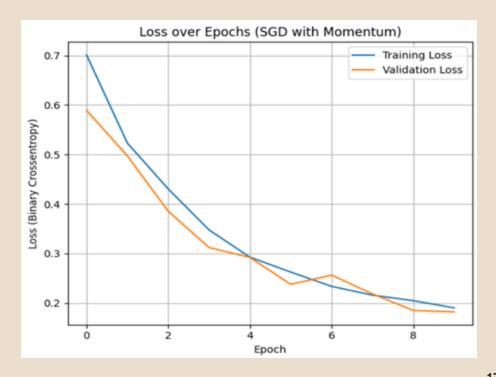
Training Accuracy: 98.7%

Cross-validation Accuracy: 98.6%

No sign of overfitting or underfitting

• Both training & validation loss steadily reduce

Optimizer	Train Loss	Train Accuracy	
Adam	0.729587	0.543890	
SGD	0.268450	0.970166	
Momentum	0.189582	0.986804	
RMSprop	0.700199	0.543890	





#### 5.3 Performance of different numbers of epochs

Best epochs for SGD with Momentum: 200 epochs

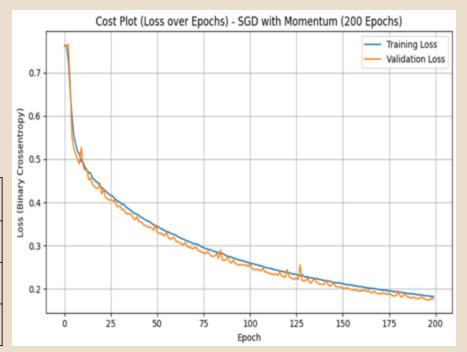
Training Accuracy: 99.6%

Cross-validation Accuracy: 99.8%

Accuracy increased 1% from the previous model

- No sign of underfitting or overfitting
- Both training & validation loss steadily reduce

Epochs	Train Loss	Train Accuracy
50	0.757383	0.543890
100	0.248084	0.991394
200	O.181778	0.995984



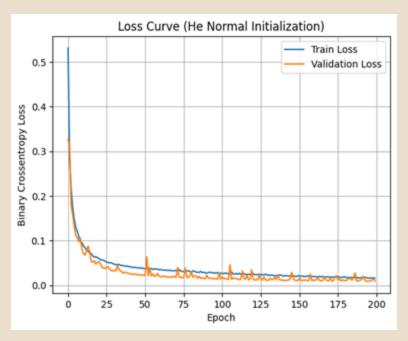


## 5.4 Performance of different Weight Initialization

Initialization	Train Accuracy	Validation Accuracy
TF Default	0.9920	0.9983
He Normal	0.9943	1.0000
Random Normal (stddev=0.05)	0.9908	1.0000
He Uniform	0.9925	1.0000

#### Best weight initialization: He Normal

- No clear improvement over baseline
- Fast drop within the first 25 epochs
- Both train & validation loss decrease smoothly
- No major train-val gap  $\rightarrow$  strong generalization
- No sign of overfitting



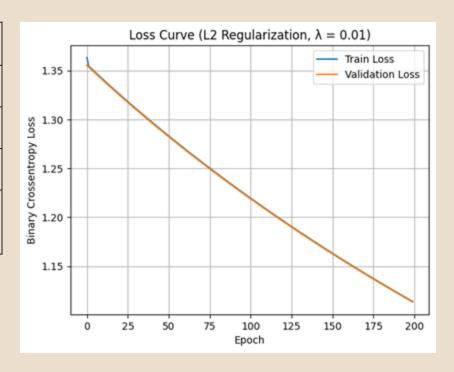


## 5.5 Performance of different L2 Regularization

Lambda (λ)	Train Accuracy	Validation Accuracy
0.000	0.9937	0.9983
0.001	0.9925	0.9948
0.010	0.9931	1.0000
0.100	0.9862	0.9948

#### Best L2 Penalty: $\lambda = 0.01$

- No clear improvement over baseline
- Slower but steady reduction in loss
- Both train & validation loss closely align
- No major train-val gap → strong generalization
- No sign of overfitting



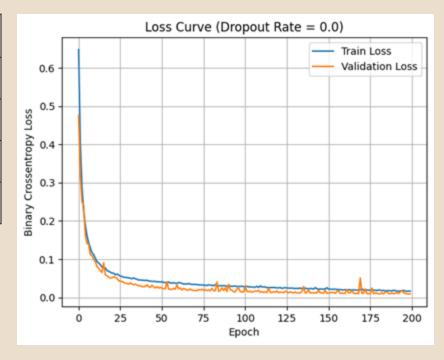


## 5.6 Performance of different Dropout Rates

Dropout Rate	Train Accuracy	Validation Accuracy	
0.0	0.9960	0.9966	
0.2	0.9925	1.0000	
0.4	0.9954	0.9966	
0.6	0.9925	1.0000	

#### Best Dropout: rate = 0.2 or 0.6

- No clear improvement over baseline
- Fast drop within the first 25 epochs
- Both train & validation loss closely align
- No major train-val gap → strong generalization
- No sign of overfitting





## 5.7 Performance of different Mixtures of L2 & Dropout

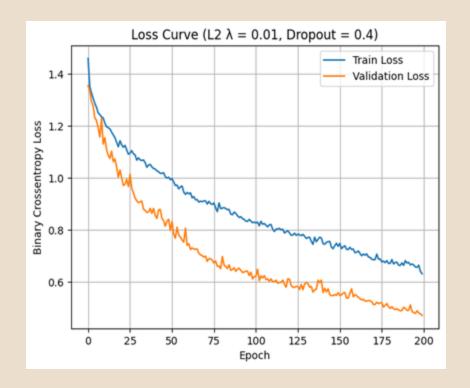
<b>L2</b> λ (O, O.O1, O.1)	<b>Dropout Rate</b> (O, O.4, O.6)	Train Accuracy	Validation Accuracy
0.00	0.0	0.9971	0.9983
0.00	0.4	0.9908	0.9966
0.00	0.6	0.9897	0.9914
0.01	0.0	0.9948	0.9966
0.01	0.4	0.9937	1.0000
0.01	0.6	0.9931	1.0000
0.10	0.0	0.9925	1.0000
0.10	0.4	0.9920	0.9983
0.10	0.6	0.9920	0.9966



#### 5.7 Performance of different Mixtures of L2 & Dropout

Best Combination: **λ** = **0.01 & Dropout** = **0.4** Train accuracy = 99.37% Validation accuracy = 100%

- The mixture did not outperform L2 or dropout regularization alone
- Train loss decreased more slowly than validation → reduce overfitting
- Validation loss always < train loss -> strong generalization
- Stable learning without performance degradation
- No sign of overfitting





# 5.8 Performance for Different Batch-normalizations

Model	Specification	Training Accuracy	Validation Accuracy
No BN	No Batch-normalization layers (baseline model)	0.9960	0.9983
BN 1	Default Batch-normalization (after each Dense hidden layer)	0.9983	0.9966
BN 2	Custom Batch-normalization with momentum=0.9, epsilon=1e-4 after each layer	0.9994	0.9983





## 5.9 - 5.12 Advanced Modeling Techniques



Early Stopping
Did not improve accuracy,
but it helps prevent overfitting

Training Accuracy: 99.31%

Validation Accuracy: 100.00%

Model Selection:

Use NN model as an example



CNN Model

Overfits quickly

Training Accuracy: 99.89%
Validation Accuracy: 99.66%
Model Selection:
Conv1, Pool1, Conv2, Pool2 layers, and a
flattened layer



**Pre-trained Model** 

Fast convergence, perfect validation

Training Accuracy: 99.94%

Validation Accuracy: 100.00%

Model Selection:

MobileNetV2



**RNN Model** 

Close to NN/CNN

Training Accuracy: 98.80%

Validation Accuracy: 99.66%

Model Selection:

GRU



Footwear



Apparel

06

# **Best Model**



#### **Final Model Selection**

#### **Final Model Architecture**

Input → Hidden Layer 1 (30 neurons, ReLU) → Hidden Layer 2 (4 neurons, ReLU) → Output (Sigmoid)

SGD with Momentum = 0.5

• Learning Rate: 0.001

• L2 Regularization (λ): 0.001

Weight Initialization: He Normal

Epochs: 200

Model Type	Train Accuracy	Validation Accuracy	
DNN (30-4)	99.6%	99.83%	
Logistic Regression	99.7%	99.3%	
DNN (7-4)	99.5%	99.83%	

Test Accuracy for DNN 30-4: 99.83%

# 07

# Managerial Implications

ootweal



Appare



## Deep Learning vs. Logistic Regression



#### **Performance Comparison**

- Logistic Regression Validation Accuracy: 99.3%
- DNN Model (30-4) Validation Accuracy: 99.83%

#### + 0.53% Accuracy Improvement

 A small improvement can bring a significant business impact at scale.



#### Why This Matters in Practice

- Fewer misclassified items → Better search & recommendations.
- More accurate tagging → Reduced manual rework.
- Less user frustration → Higher conversion rate
   & trust.
- Improved scalability for future product expansion.







#### From Model Accuracy to Business Value

#### **Business Context**

Our platform processes 10,000+ new product images daily. Each classification error has downstream impacts across:

- Manual correction labor
- Customer service load
- Misdirected recommendations
- User frustration & churn risk

Quantified Impact				
Model	Error Rate	Errors/Day	Cost/Day	
Logistic Regression	0.7%	70	\$140	
Final DNN (30-4)	0.17%	17	\$34	
Daily Cost Saving	_	↓ 53	\$106	
Monthly Saving	_	_	~\$3,180	

Assumes \$2 per misclassification (labor, rework, lost revenue, etc.)

#### **Beyond the Numbers: Strategic Benefits**

- Scalability Handles growth without adding headcount.
- Customer Experience & Trust Better data →
  easier discovery → higher conversion.
- Competitive Advantage Faster category expansion and market response.





# THANK You!

Footwear



Apparel

