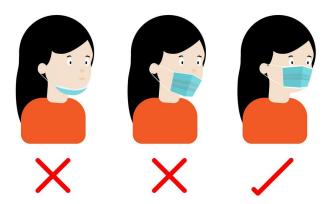
Face Mask Detection

Shania Dhani Michelle Lucero Xuejin Gao



Problem Description

Mask Restrictions in public areas & Contact Tracing for COVID-19



State of the Art/Related Work

"A hybrid deep transfer learning model with machine learning methods for face mask detection in the era of the COVID-19 pandemic" (Loey, Manogaran, Taha and Khalifa)

Does not account for wearing masks incorrectly

Has up to a 100% accuracy across one of the three tested datasets

Member

Role

Michelle

Data Preprocessing and SVM

Shania

KNN and Decision Tree Models

Xuejin

CNN and Naive Bayes Models

Data Preprocessing



KNN Progression



No Hyperparameter Tuning

~15 mins

Reduced images to 64X64 pixels to reduce dimensionality in the dataset.

GridSearchCV
Hyperparameter Tuning

82%

Not Normalized

Phase 1

Manhattan, Neighbors: 5

~15 hours; Memory Intensive

Computationally Expensive for Predictions

Dimensionality
Reduction Phase 2

~83%

Normalized Dataset

PCA transformation w/ 90% variance preservation over the training set RandomizedSearchCV
Hyperparameter
Tuning Phase 3

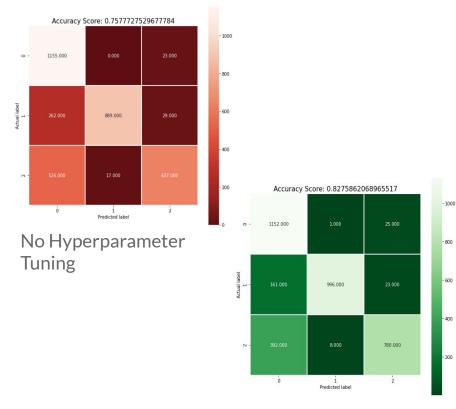
86.7%

Normalized Dataset

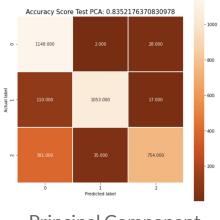
Manhattan, Neighbors: 2, weight: distance

Less computationally expensive + memory intensive

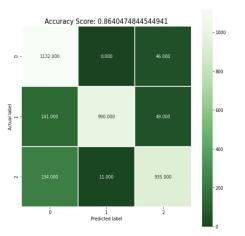
KNN Model Evaluation



GridSearchCV Hyperparameter Tuning



Principal Component Analysis



RandomizedSearchCV Hyperparameter Tuning

Decision Trees Progression



No Hyperparameter Tuning

Fast

Default Scikit Parameters

Normalized

Tree is more shallow

Dimensionality Reduction: PCA

Fast

Transformation improved accuracy

Normalized

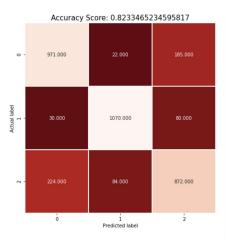
Hyperparameter Tuning

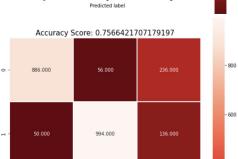
Fast

Gini, max depth = 10, max features = 1138

Searching for the model's best parameters was a ~1 hour computation

Decision Trees Model Evaluation





Predicted label

797.000

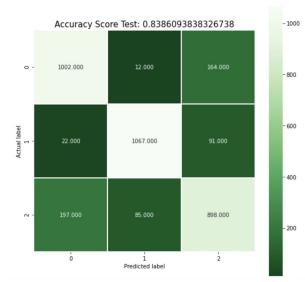
- 200

82% No hyperparameter tuning

- 1000

- 800



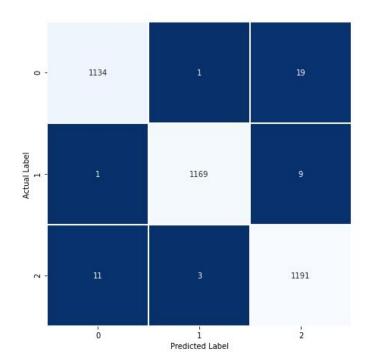


84%, Max-Depth=10, Max Features=1138

Hyperparameter		Tuning Class			
			recall	f1-score	support
	0	0.82	0.85	0.84	1178
	1	0.92	0.90	0.91	1180
	2	0.78	0.76	0.77	1180
accur	acy			0.84	3538
macro	avg	0.84	0.84	0.84	3538
weighted	avg	0.84	0.84	0.84	3538

CNN Metrics

	precision	recall	f1-score	support
0	0.99	0.98	0.99	1154
1	1.00	0.99	0.99	1179
2	0.98	0.99	0.98	1205
accuracy			0.99	3538
macro avg	0.99	0.99	0.99	3538
weighted avg	0.99	0.99	0.99	3538



SVM Metrics

Evaluate performance for using 100% of the dataset

```
### 1. Get and print a baseline accuracy score.
y_pred = model_100.predict(X_test)
accuracy = model_100.score(X_test, y_test)
print("Accuracy %f" % accuracy)
metrics.accuracy_score(y_true=y_test, y_pred=y_pred)
```

Accuracy 0.961556

5]: 0.9615558570782451

M	<pre>print(metrics.classification_report(y_test,</pre>	y_pred))
---	--	----------

	precision	recall	f1-score	support
0	0.95	0.96	0.96	1489
1	0.99	0.98	0.99	1466
2	0.94	0.94	0.94	1467
accuracy			0.96	4422
macro avg	0.96	0.96	0.96	4422
weighted avg	0.96	0.96	0.96	4422

Evaluate performance for using 75% of the dataset

```
### 1. Get and print a baseline accuracy score.
y_pred = model_75.predict(X_test)
accuracy = model_75.score(X_test, y_test)
print("Accuracy %f" % accuracy)
metrics.accuracy_score(y_true=y_test, y_pred=y_pred)
```

Accuracy 0.951161

)]: 0.9511606873681037

Evaluate performance for using 50% of the dataset

```
### 1. Get and print a baseline accuracy score.
y_pred = model_50.predict(X_test)
accuracy = model_50.score(X_test, y_test)
print("Accuracy %f" % accuracy)
metrics.accuracy_score(y_true=y_test, y_pred=y_pred)
```

Accuracy 0.939846

Evaluate performance for using 25% of the dataset

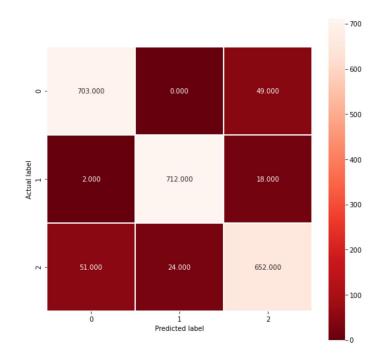
```
### 1. Get and print a baseline accuracy score.
y_pred = model_25.predict(X_test)
accuracy = model_25.score(X_test, y_test)
print("Accuracy %f" % accuracy)
metrics.accuracy_score(y_true=y_test, y_pred=y_pred)
```

Accuracy 0.933996

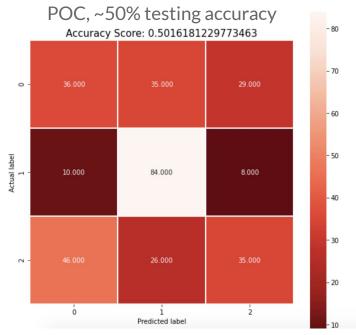
5]: 0.933996383363472

SVM Metrics

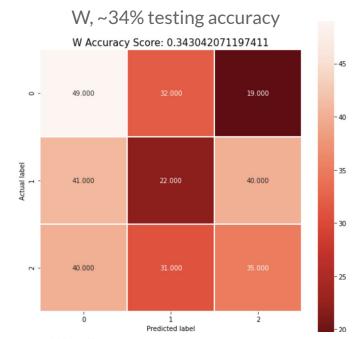
	precision	recall	f1-score	support
0	0.93	0.93	0.93	752
1	0.97	0.97	0.97	732
2	0.91	0.90	0.90	727
accuracy			0.93	2211
macro avg	0.93	0.93	0.93	2211
weighted avg	0.93	0.93	0.93	2211



KNN Model Bias Assessment

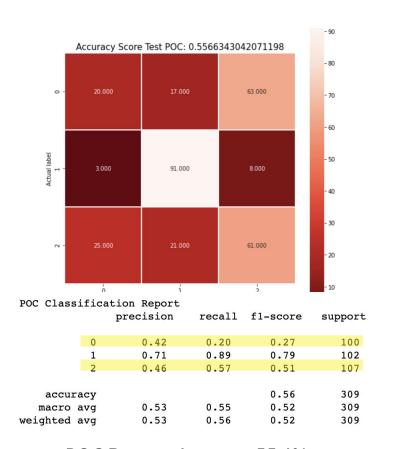


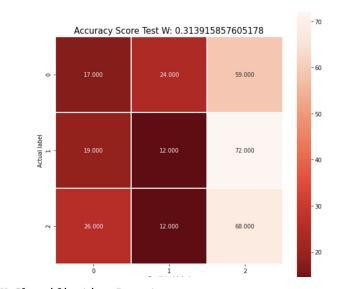
Classification		Report POC precision		set f1-score	support
	0	0.39	0.36	0.37	100
	1	0.58	0.82	0.68	102
	2	0.49	0.33	0.39	107
accur macro weighted	avg	0.49 0.49	0.50 0.50	0.50 0.48 0.48	309 309 309



Classification		Report W Test Dataset				
		precision	recall	f1-score	support	
	0	0.38	0.49	0.43	100	
	1	0.26	0.21	0.23	103	
	2	0.37	0.33	0.35	106	
accur	acy			0.34	309	
macro	avg	0.34	0.34	0.34	309	
weighted	avg	0.34	0.34	0.34	309	

Decision Trees Bias Assessment



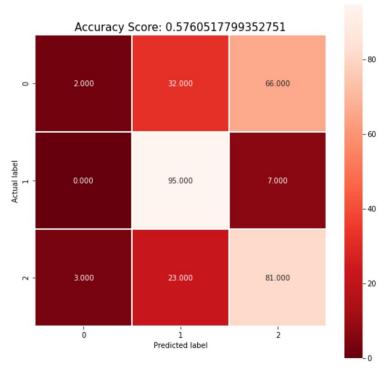


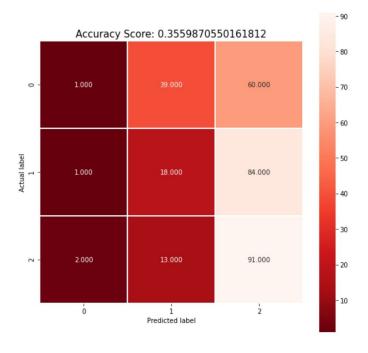
W Classifi	cati	on Report precision	recall	f1-score	support
	0	0.27	0.17	0.21	100
	1	0.25	0.12	0.16	103
	2	0.34	0.64	0.45	106
accura	су			0.31	309
macro a	vg	0.29	0.31	0.27	309
weighted a	vg	0.29	0.31	0.27	309

POC Dataset Accuracy 55.6%

W Dataset Accuracy 31.4.%

SVM Bias Assessment





POC Dataset Accuracy 57.6%

W Dataset Accuracy 35.6%

CNN Bias Assessment

POC: ~60% accuracy W: ~36% accuracy

Differences between Images



Image from our training data of class "incorrectly wearing mask"



Image from our testing W data of class "incorrectly wearing mask"

POSSIBLE REASONS BIAS ASSESSMENT PERFORMANCE:

- We overfitted our models to the training data
- The training images contain noise or features that differ dramatically from the new instances
- More Feature Selection was needed to reduce the importance of irrelevant features
- Simulated face masks in our training data, negatively affected our models ability to correctly classify certain types of instances

What We Learned

- Feature Set Is Important.
 - Too many "unimportant" features can be noisy,
 - Too many features can be computationally expensive and memory intensive for certain models (KNN, SVM)
- Dataset Collection and Choice is Important.
 - Be picky about your training dataset.
 - Actively test more often for biases in dataset
- Hyperparameter Tuning is Hard.

The End

References

- Loey, M., Manogaran, G., Taha, M., & Khalifa, N. (2021). A hybrid deep transfer learning
 - model with machine learning methods for face mask detection in the era of the COVID-19 pandemic.
 - Measurement : journal of the International Measurement Confederation, 167, 108288.
 - https://doi.org/10.1016/j.measurement.2020.108288

Evaluation

"99.64% accuracy, with up to 100% accuracy on one of the three different datasets used in the baseline research."

We will use the performance metrics gathered on the:

- SVM
- KNN
- CNN
- Naive Bayes
- Decision Trees

To make our own ML Model and compare it to our baseline study.

Approach

We plan to use a combination of different datasets available to create a new dataset that is labelled *for mask v. no mask v. incorrect wearing of a mask.*

- KNN
- Different types of CNN to gauge which models are the best predictors.

We hope to create our own face-detection model.