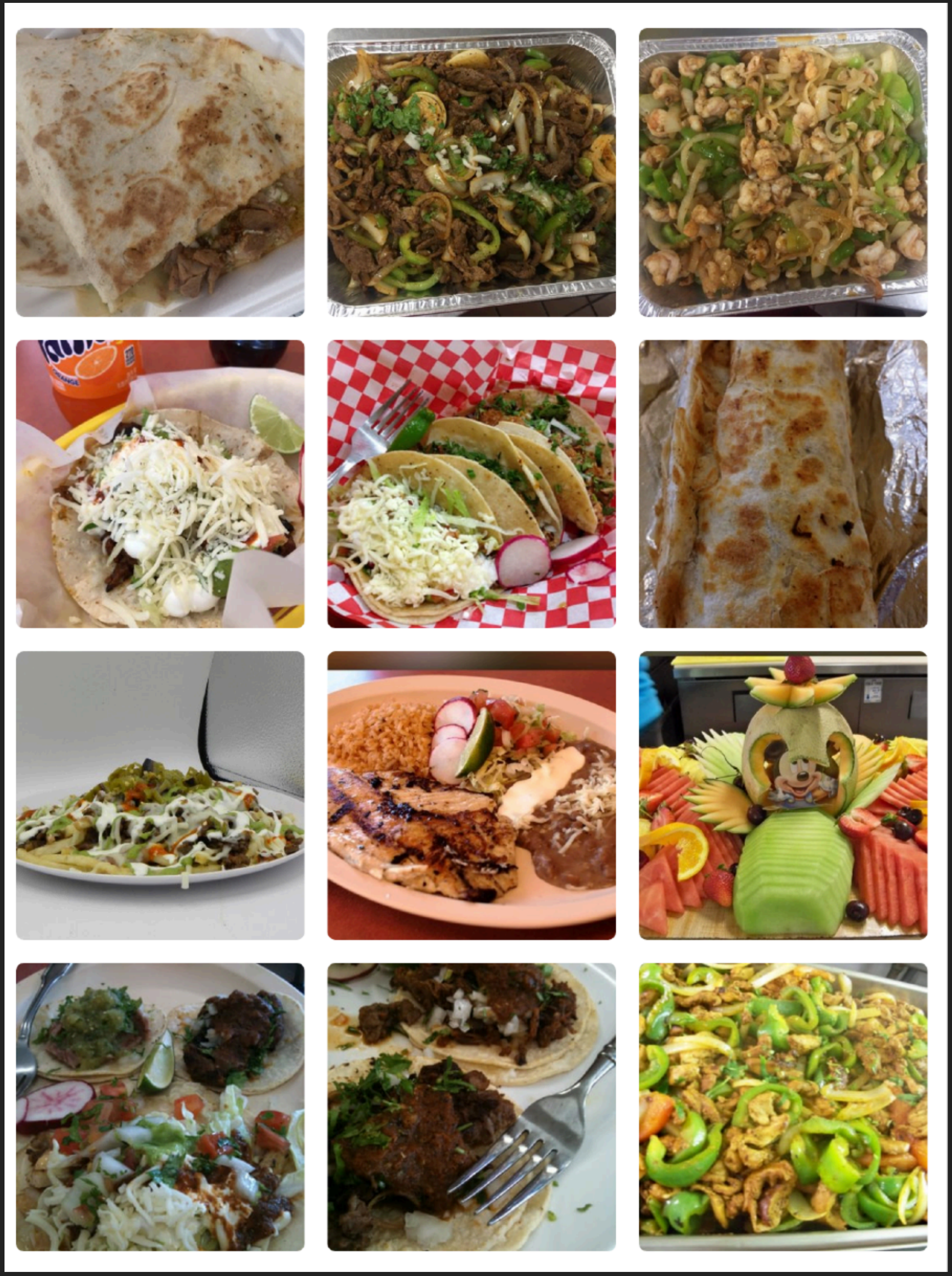
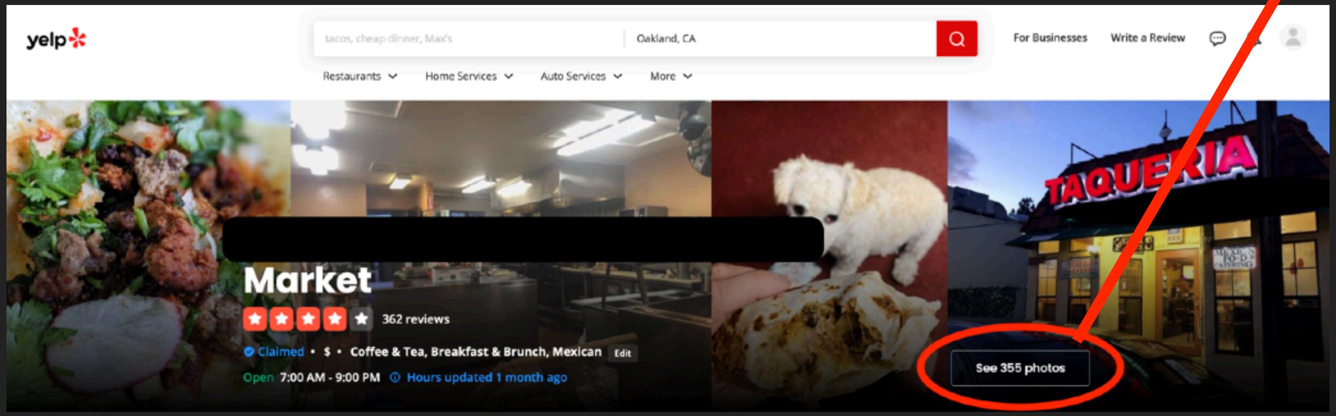
A BETTER <u>SORT</u> OF YELP PHOTOS

PROBLEM STATEMENT

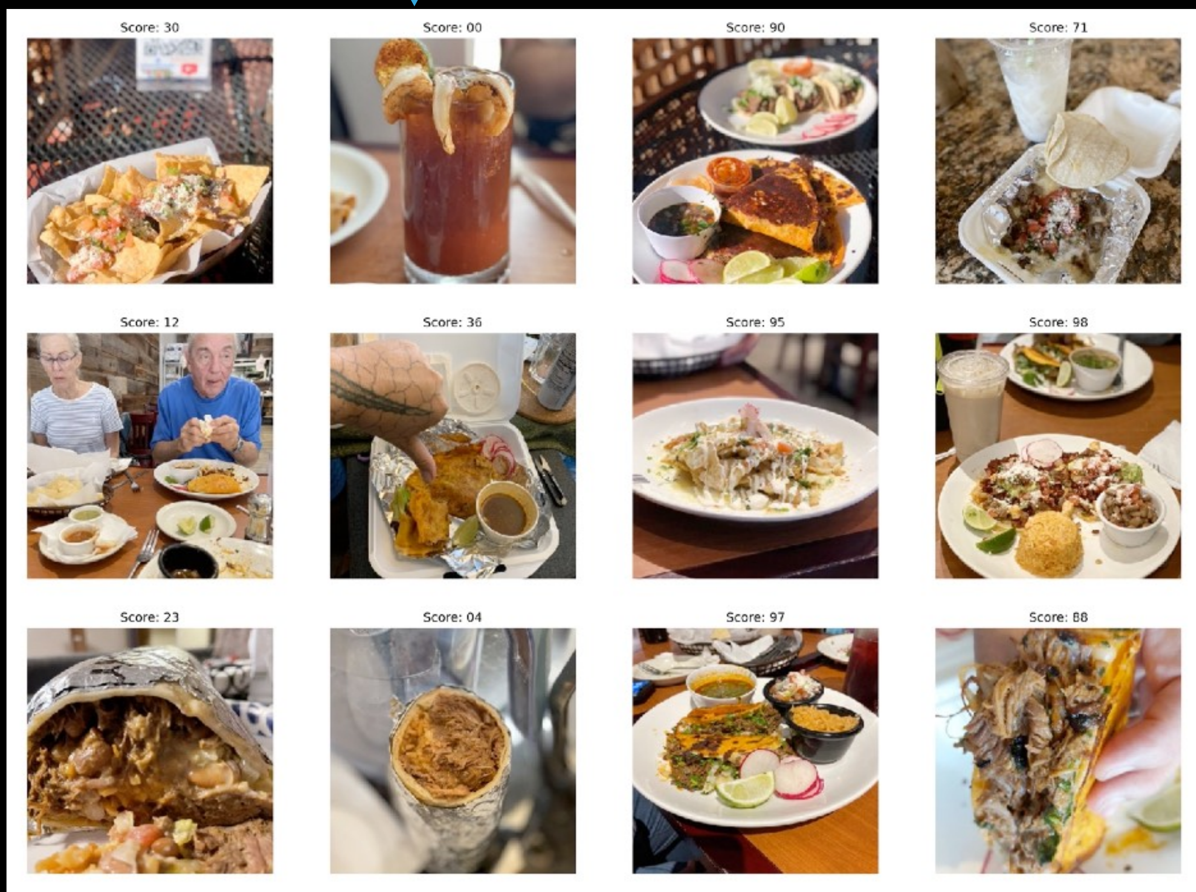
Why are the photos in many Yelp restaurant galleries still poor quality? App users and owners deserve a better sort option.



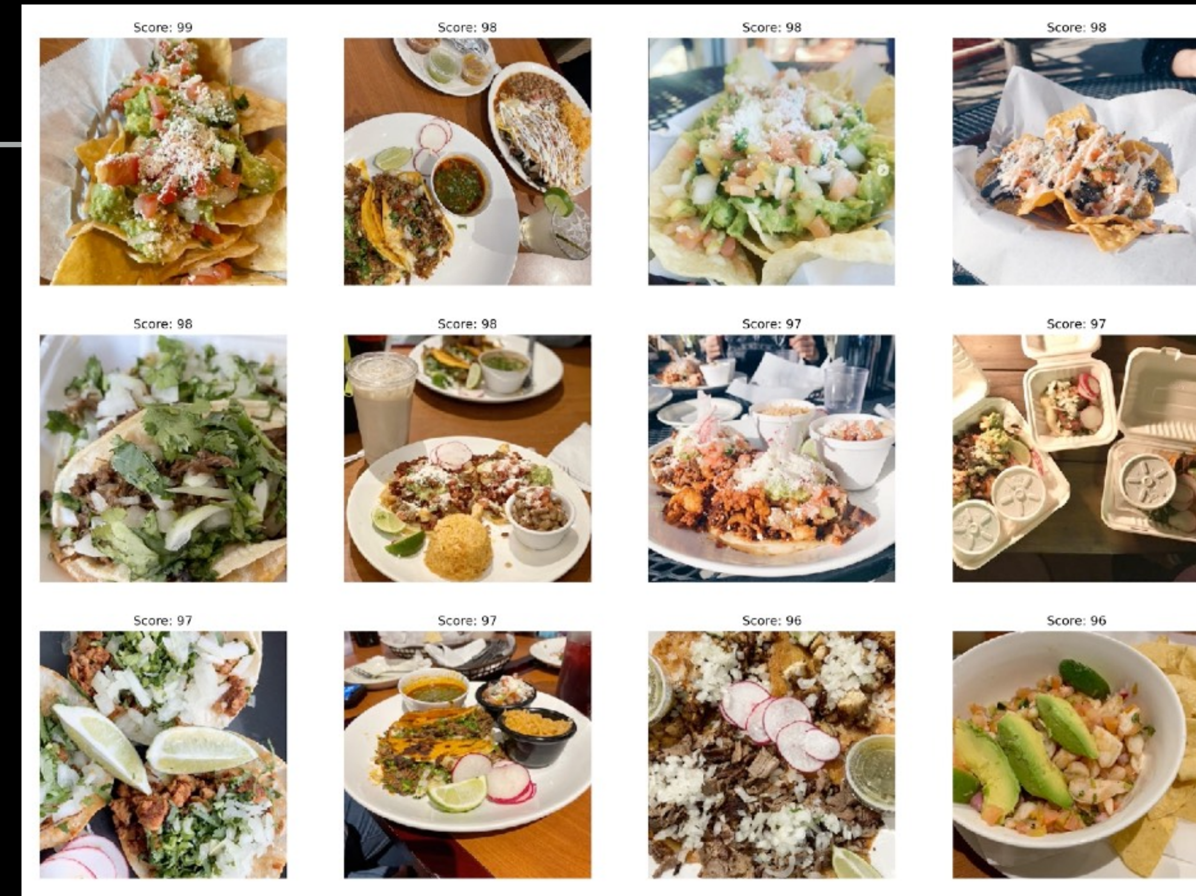


USING MACHINE LEARNING TO SORT

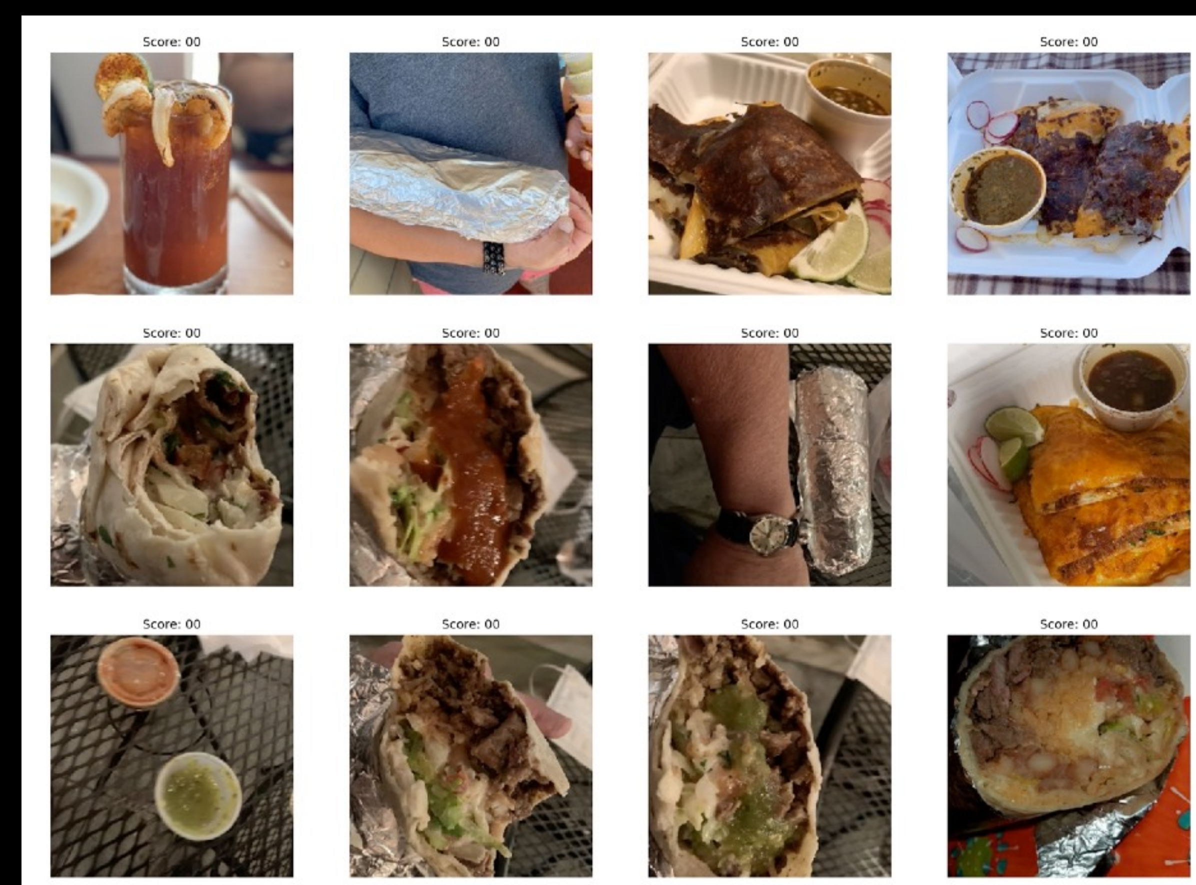
ORIGINAL GALLERY ORDER



SORTS HIGH QUALITY PHOTOS TO THE TOP.



SORTS POOR QUALITY PHOTOS TO THE BOTTOM



BACKGROUND

Sources

METHODS

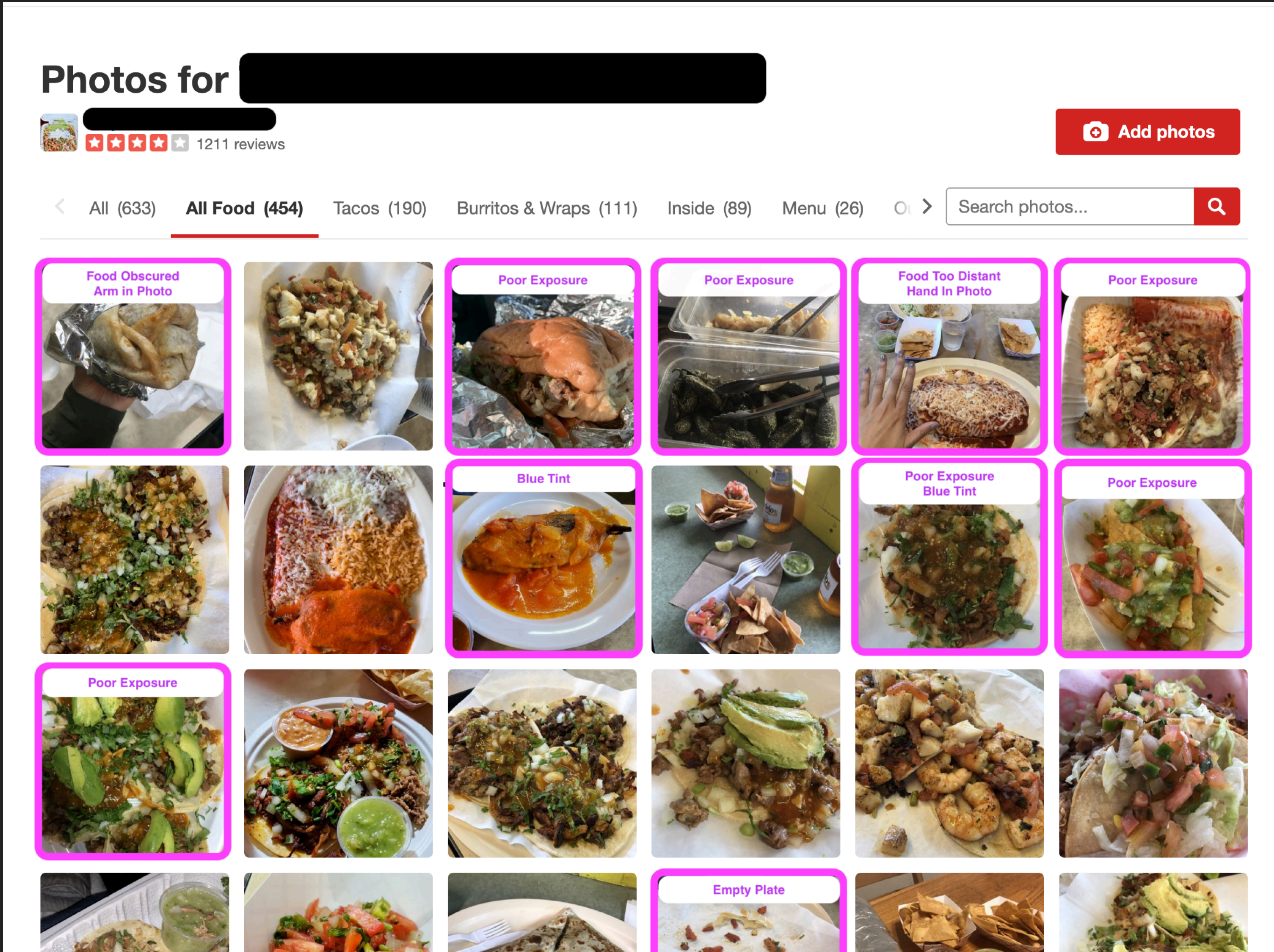

Photos for [redacted]
[redacted]
1211 reviews
Add photos
All (633)
All Food (454)
Tacos (190)
Burritos & Wraps (111)
Inside (89)
Menu (26)
Search photos...
Food Obscured
Arm in Photo
Poor Exposure
Poor Exposure
Food Too Distant
Hand In Photo
Poor Exposure
Blue Tint
Poor Exposure
Blue Tint
Poor Exposure
Poor Exposure
Empty Plate

PHOTO CRITERIA

- Focus: Subject in focus.

Label: [good]

Label: [bad]

PHOTO CRITERIA

- Focus: Subject in focus.
- Exposure: Even

Label: [good]

Label: [bad]

PHOTO CRITERIA

- Focus
- Exposure
- Subject
-

Label: [good]

Label: [bad]

PHOTO CRITERIA

- Focus
- Exposure
- Subject
- Color

Label: [good]

Label: [bad]

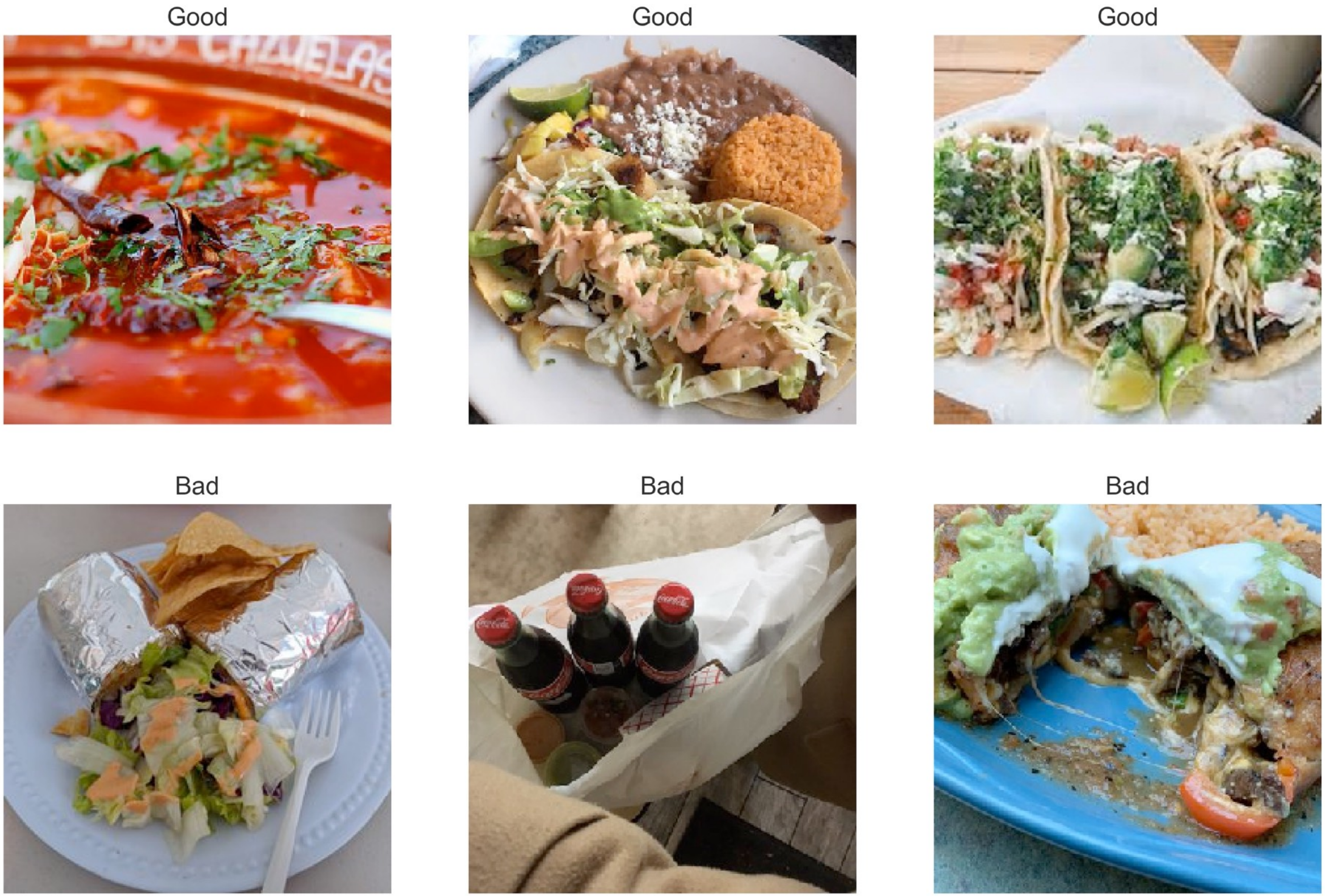
PHOTO CRITERIA

- Focus
- Exposure
- Subject
- Color
- Pattern / Composition

Label: [good]

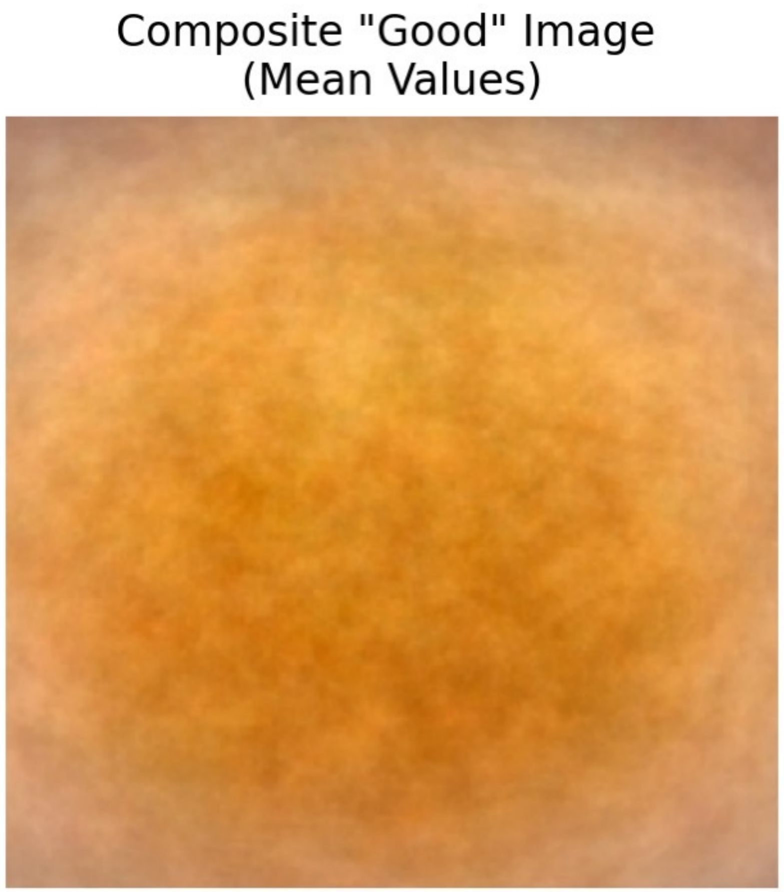
Label: [bad]

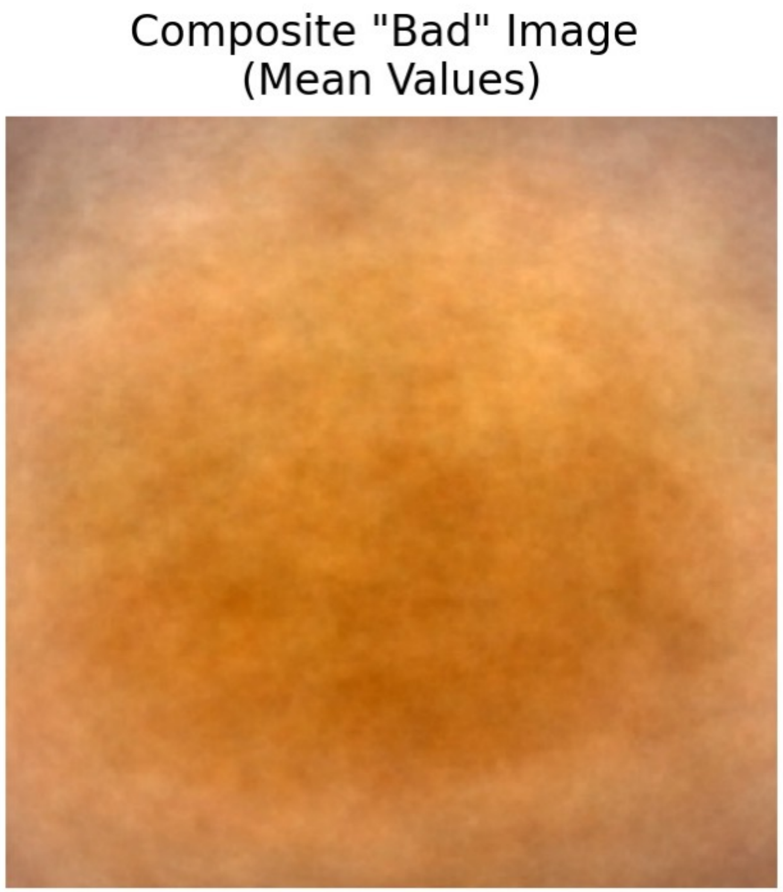
DATA VISUALIZATION


Good
Good
Good
Bad
Bad
Bad

DATA VISUALIZATION

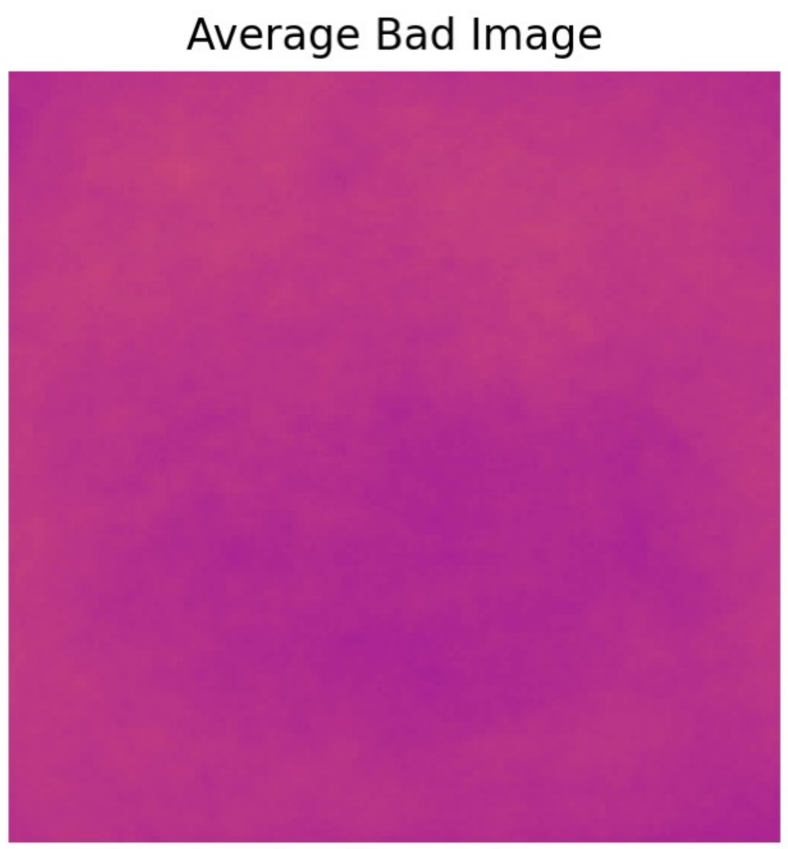
- Composite image for each class (mean values)





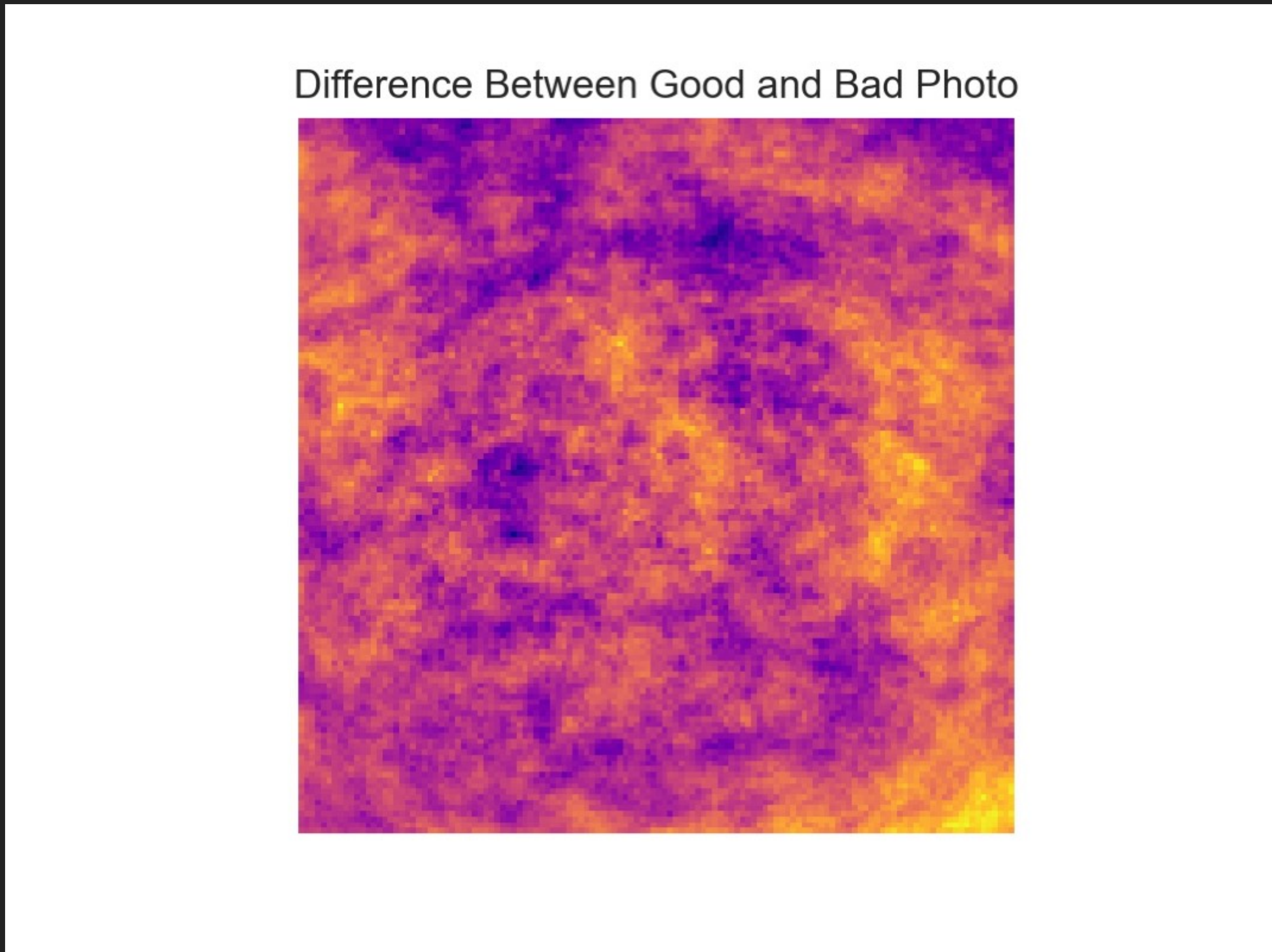
DATA VISUALIZATION

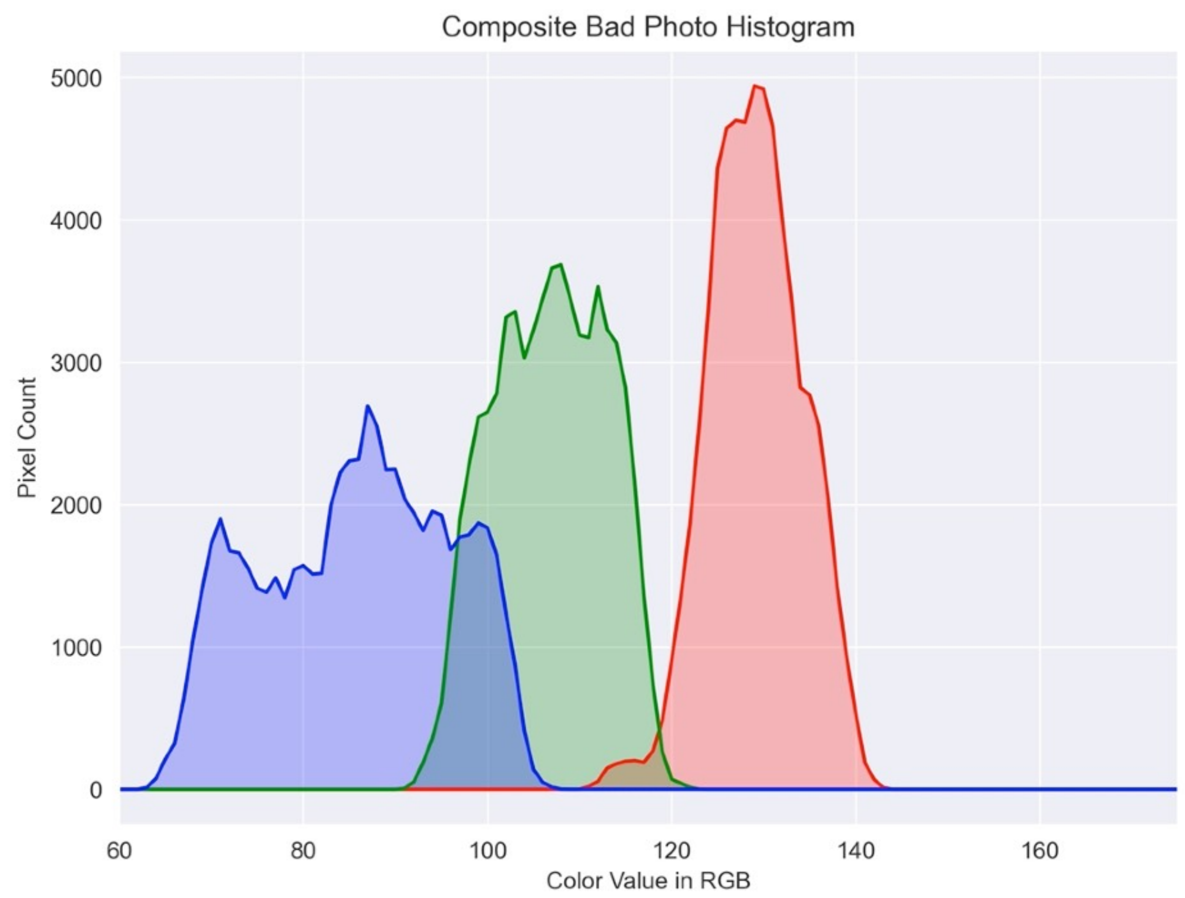
- Average Grayscale Image Per Class



DATA VISUALIZATION

- Contrast Image (Difference Between Average "Good" Image And Average "Bad" Image)



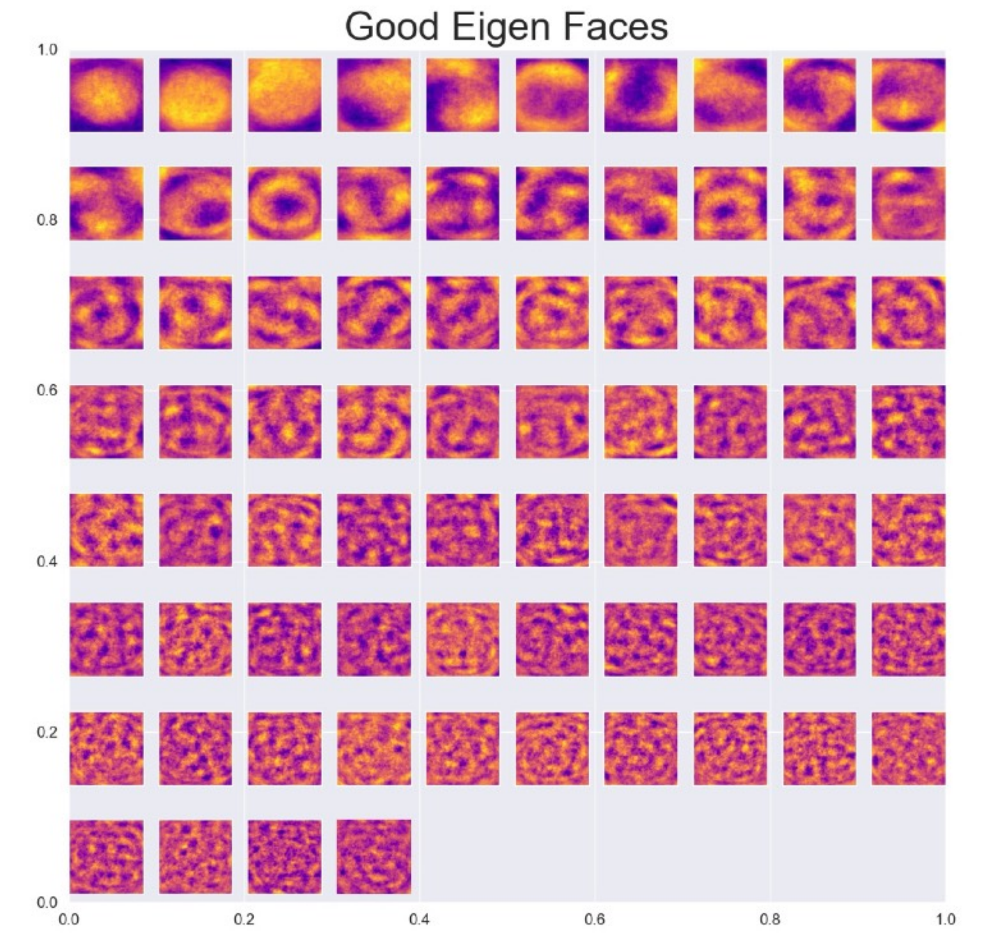


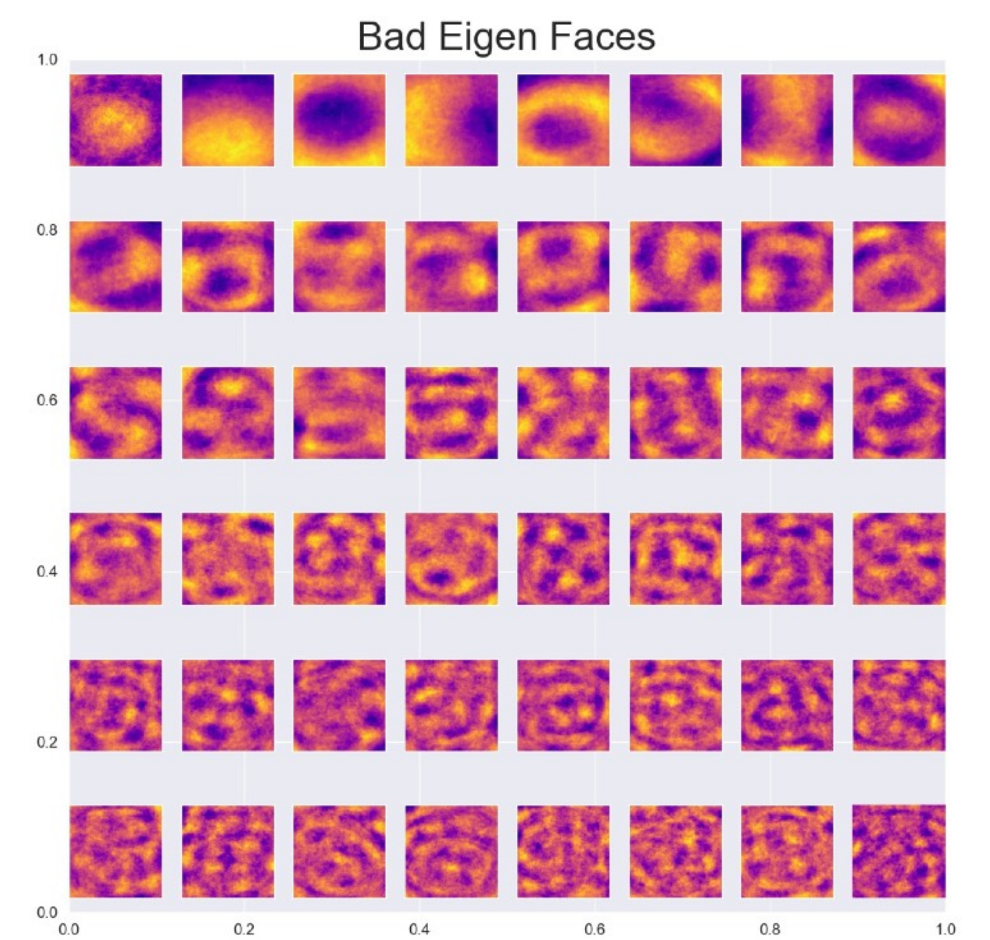
DATA VISUALIZATION

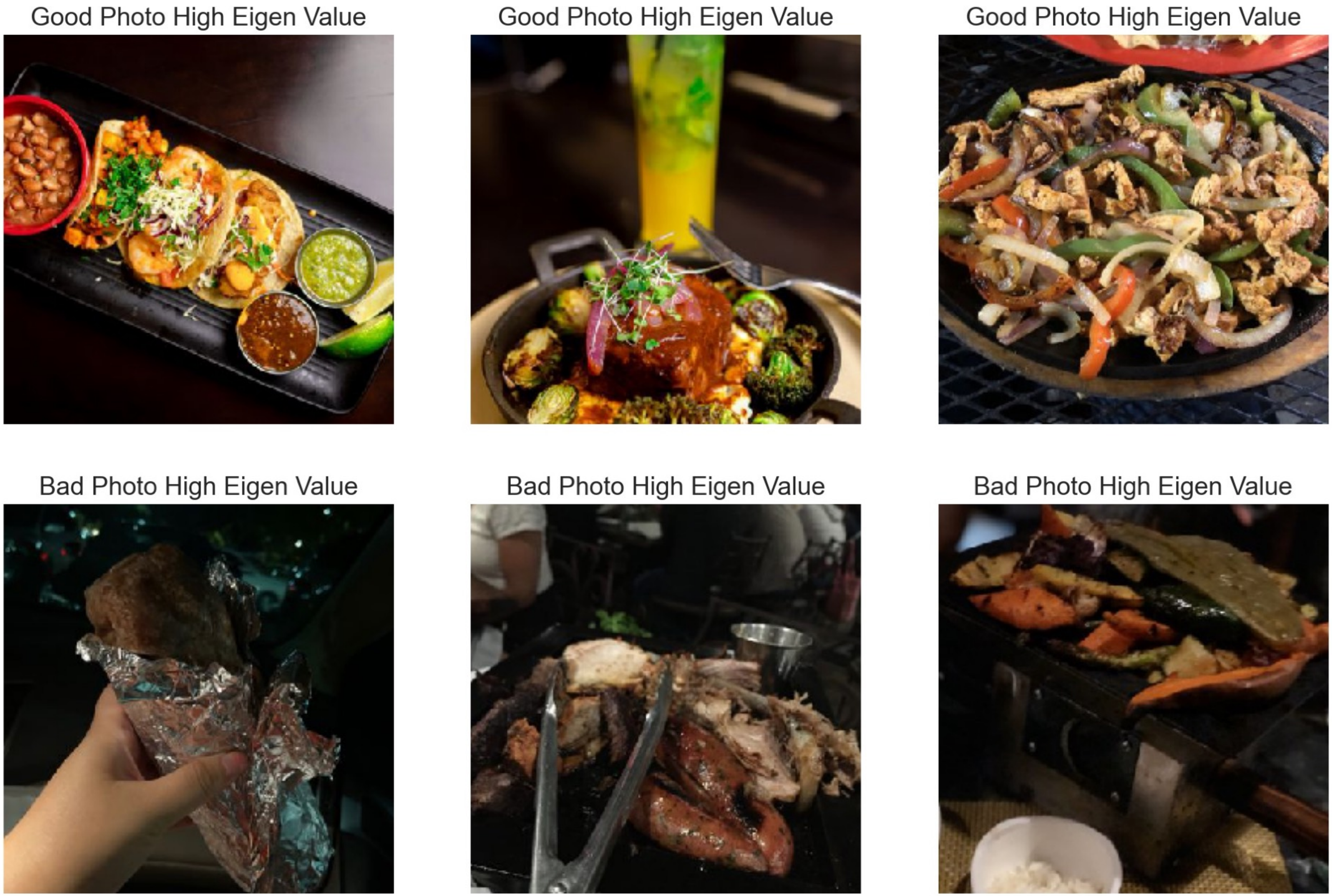
- Composite Histograms for Each Class

DATA VISUALIZATION

- Principle Components Analysis
- Makes Composites of Each Class That Explain 70% of the Variance
- Sometimes Called "Eigen Faces"; used in facial recognition research.






Good Photo High Eigen Value
Good Photo High Eigen Value
Good Photo High Eigen Value
Bad Photo High Eigen Value
Bad Photo High Eigen Value
Bad Photo High Eigen Value

MODELING

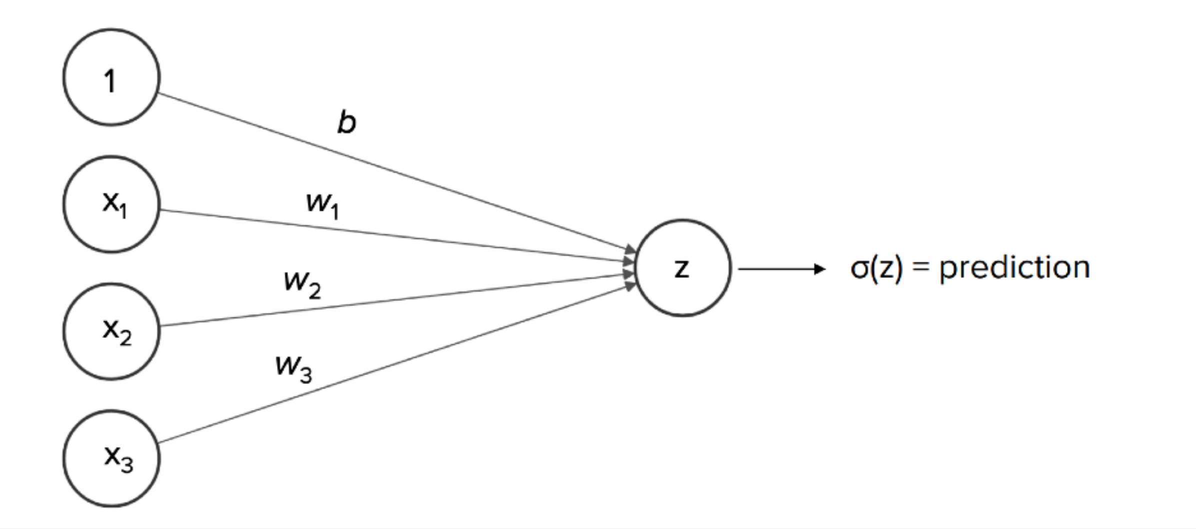
CONVOLUTIONAL NEURAL NETS (CNN)

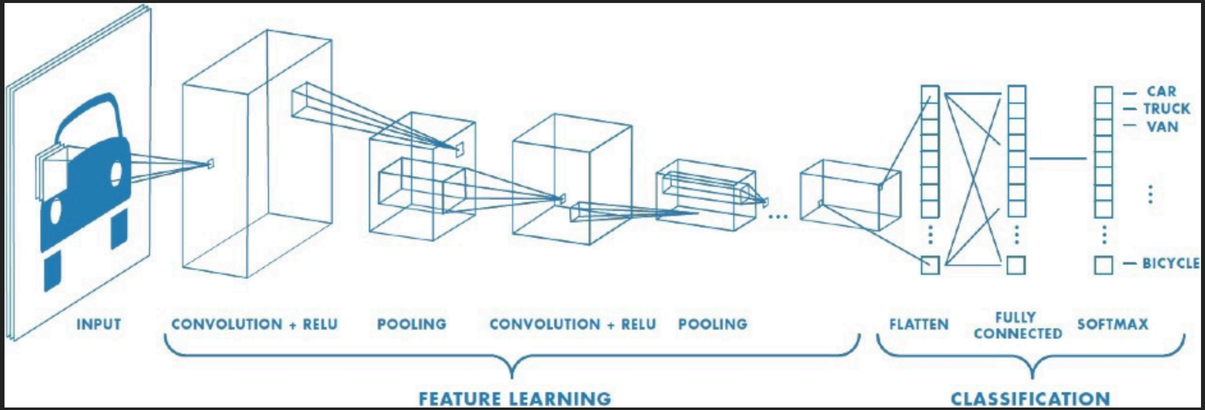
- What are they?
- CNNs are some of the best classifiers for images
- Two Methods Used. Two Models for EACH:
  - CNN from Scratch (Model 1, Model 2)
  - CNN with Transfer Learning (Model 3, Model 4)

$$p = \sigma\left(b + w_1 x_1 + w_2 x_2 + w_3 x_3\right)$$

Curvy part

Linear part



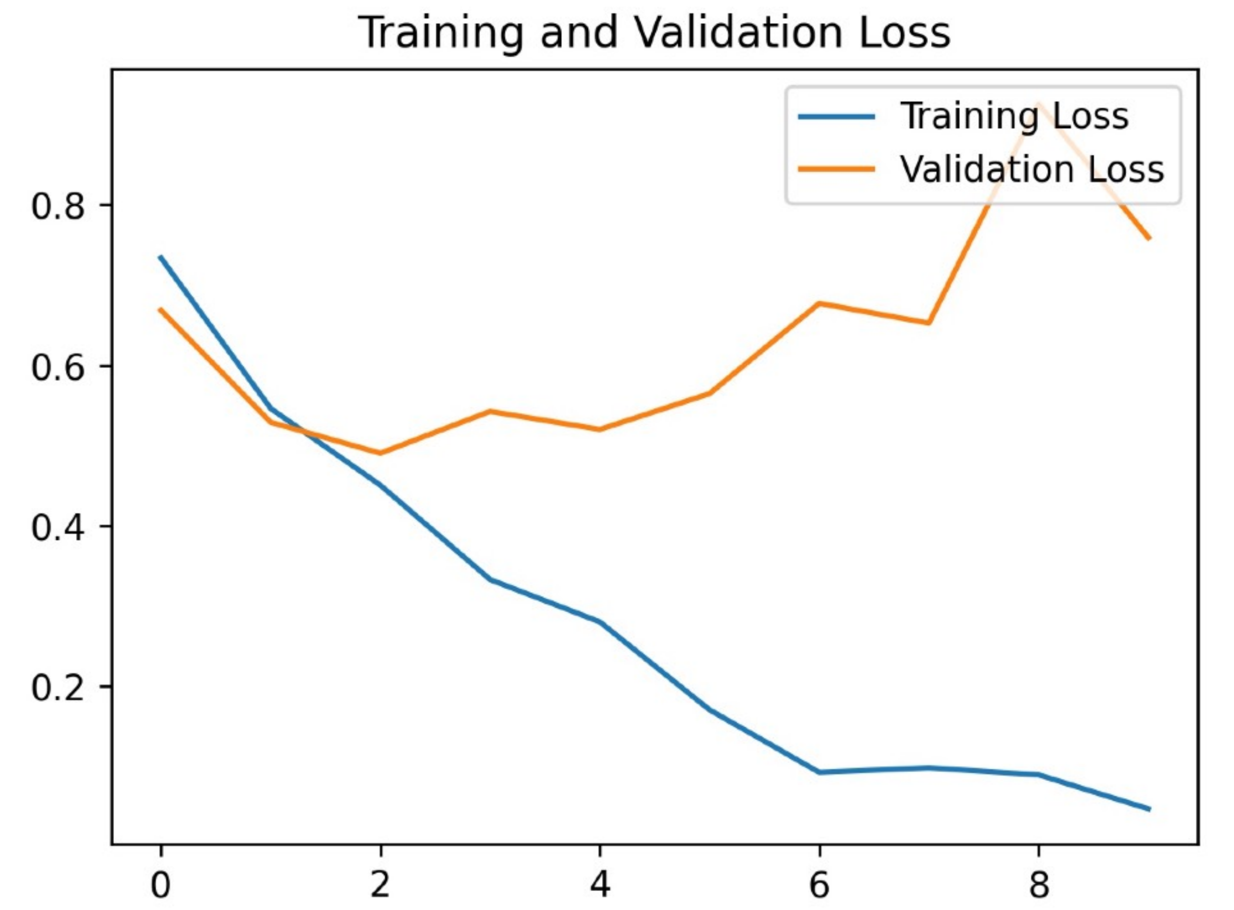


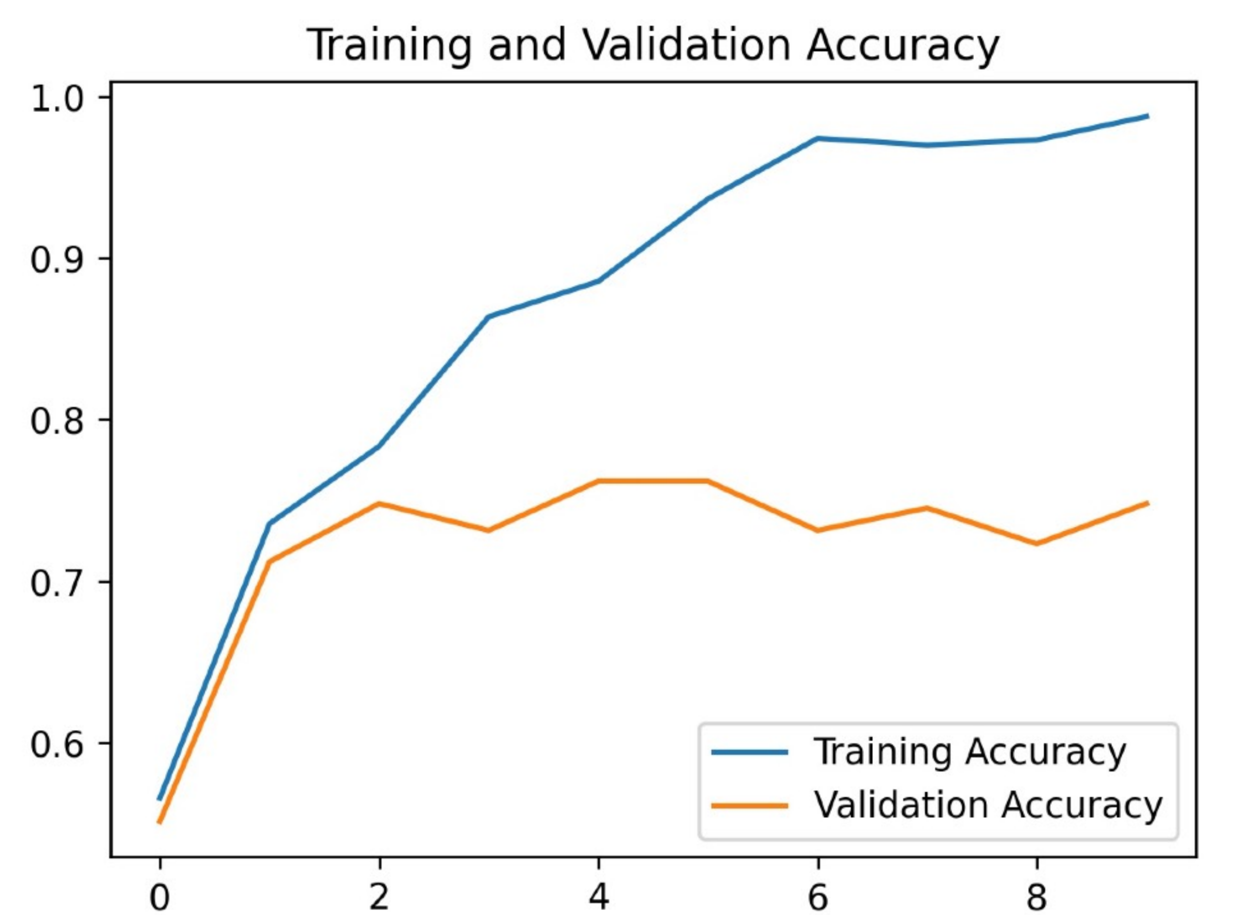
[Source]

MODEL 1: 76% ACC

Batch size: 16, Image size: 256x256

```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling_8 (Rescaling)     (None, 256, 256, 3)       0

 conv2d_15 (Conv2D)          (None, 256, 256, 16)      448

 max_pooling2d_15 (MaxPoolin  (None, 128, 128, 16)     0
 g2D)

 conv2d_16 (Conv2D)          (None, 128, 128, 32)      4640

 max_pooling2d_16 (MaxPoolin  (None, 64, 64, 32)       0
 g2D)

 conv2d_17 (Conv2D)          (None, 64, 64, 64)        18496

 max_pooling2d_17 (MaxPoolin  (None, 32, 32, 64)       0
 g2D)

 flatten_5 (Flatten)         (None, 65536)             0

 dense_10 (Dense)            (None, 128)               8388736

 dense_11 (Dense)            (None, 1)                 129

=================================================================
Total params: 8,412,449
Trainable params: 8,412,449
Non-trainable params: 0
```



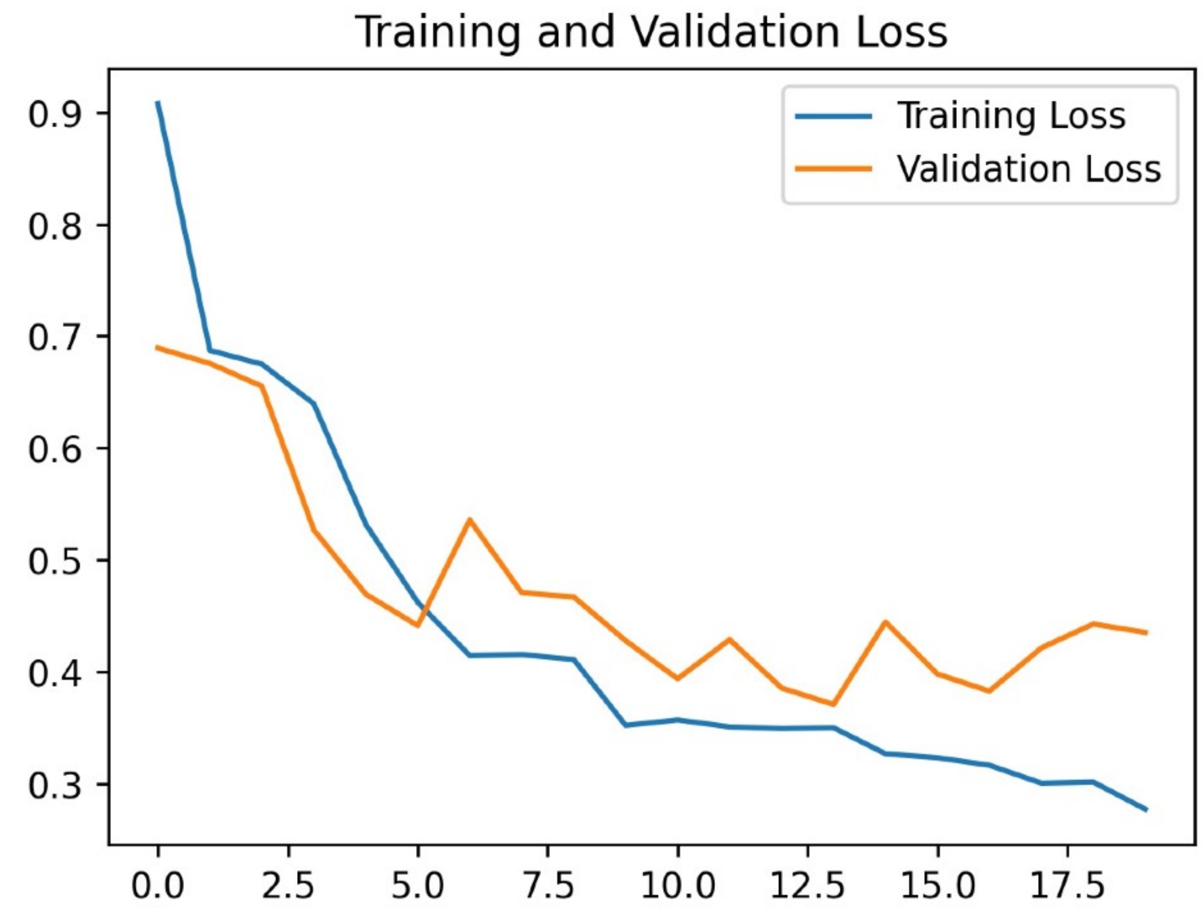


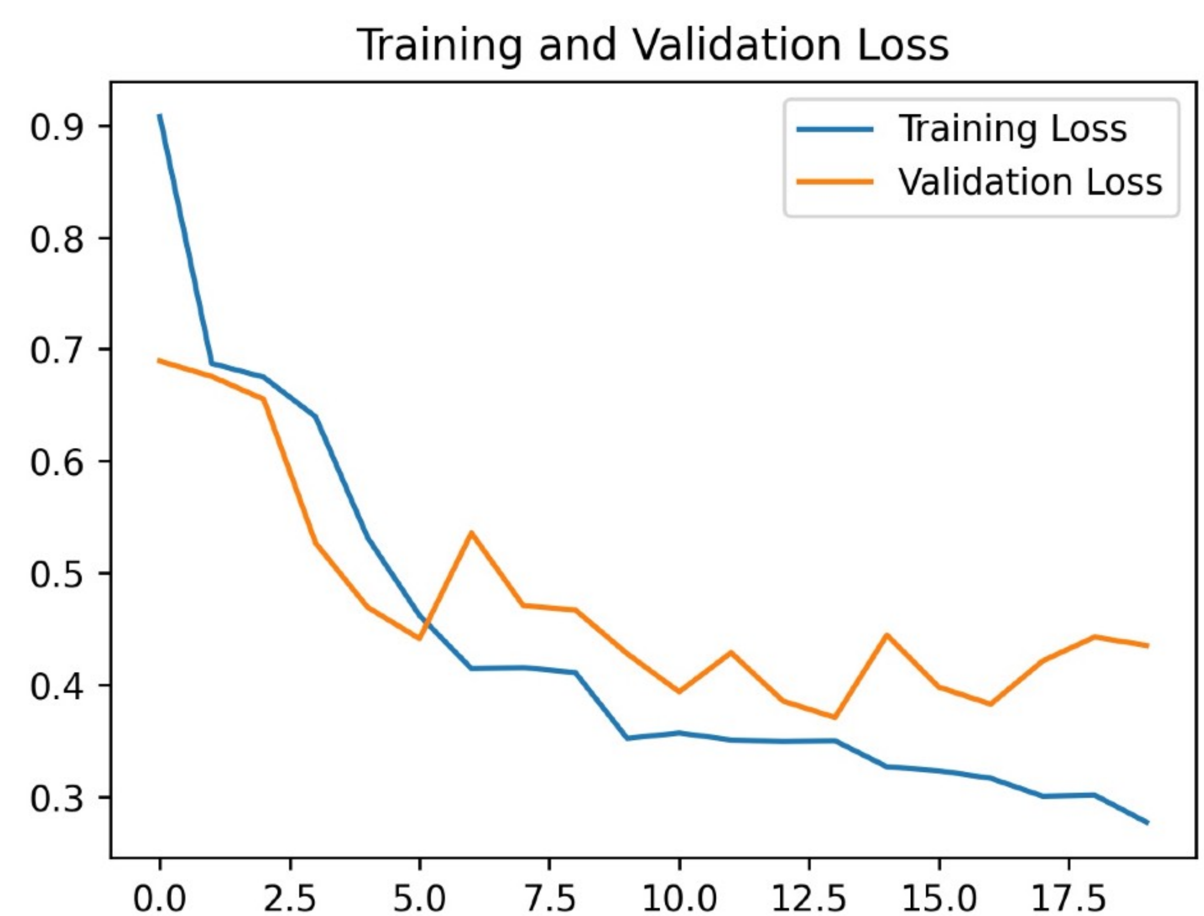
MODEL 2: 82% ACC

Batch size: 16, Image size: 256x256

Adds Image Augmentation & Dropout

```
Model: "sequential_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 sequential_7 (Sequential)   (None, 256, 256, 3)       0

 rescaling_9 (Rescaling)     (None, 256, 256, 3)       0

 conv2d_18 (Conv2D)          (None, 256, 256, 16)      448

 max_pooling2d_18 (MaxPoolin  (None, 128, 128, 16)     0
 g2D)

 conv2d_19 (Conv2D)          (None, 128, 128, 32)      4640

 max_pooling2d_19 (MaxPoolin  (None, 64, 64, 32)       0
 g2D)

 conv2d_20 (Conv2D)          (None, 64, 64, 64)        18496

 max_pooling2d_20 (MaxPoolin  (None, 32, 32, 64)       0
 g2D)

 dropout (Dropout)           (None, 32, 32, 64)        0

 flatten_6 (Flatten)         (None, 65536)             0

 dense_12 (Dense)            (None, 128)               8388736

 dense_13 (Dense)            (None, 1)                 129

=================================================================
Total params: 8,412,449
Trainable params: 8,412,449
Non-trainable params: 0
_________________________________________________________________
```

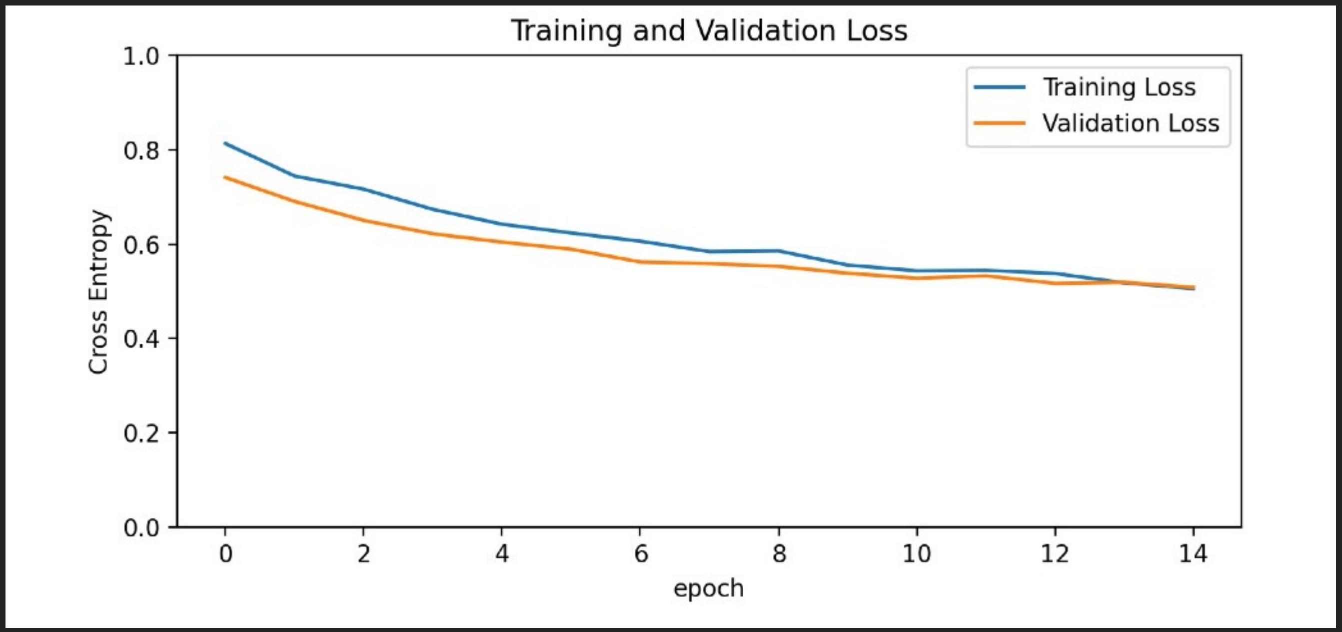


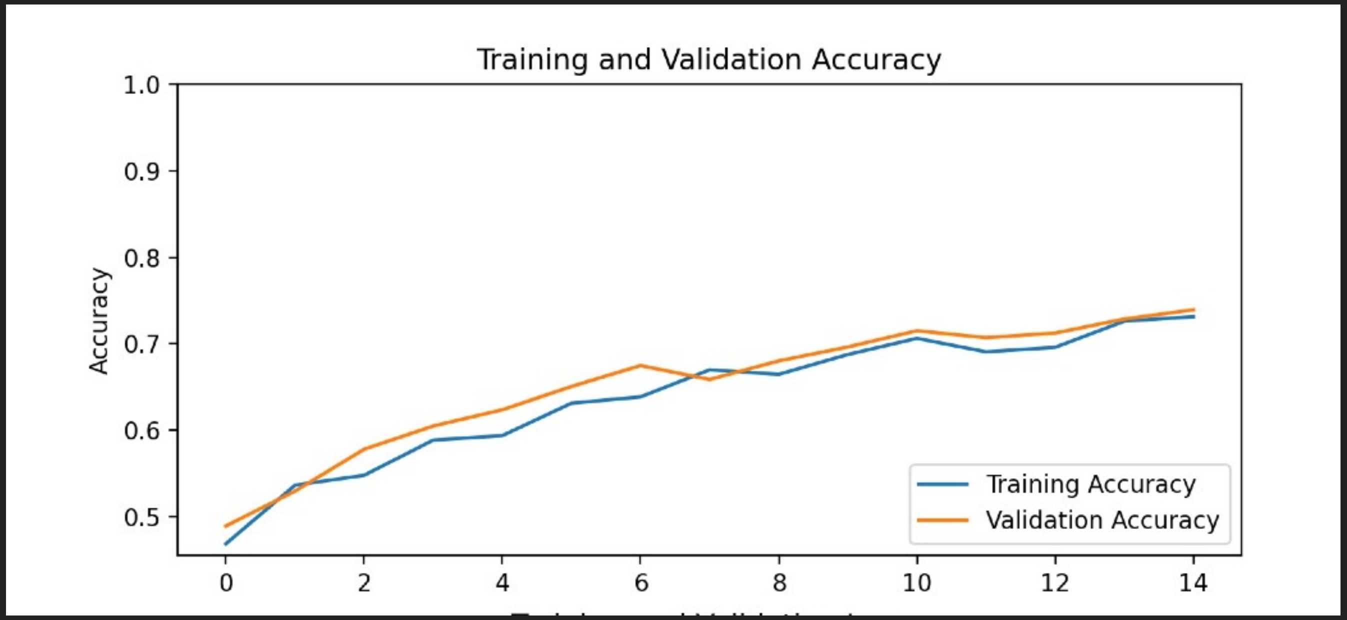


MODEL 3: ~73% ACC

~73% on Validation Data after 15 epochs

- A feature extraction transfer learning model
- Uses MobileNet V2 from Google (1.4 M photos, 1000 classes)
- Takes the top off and applies to this data.

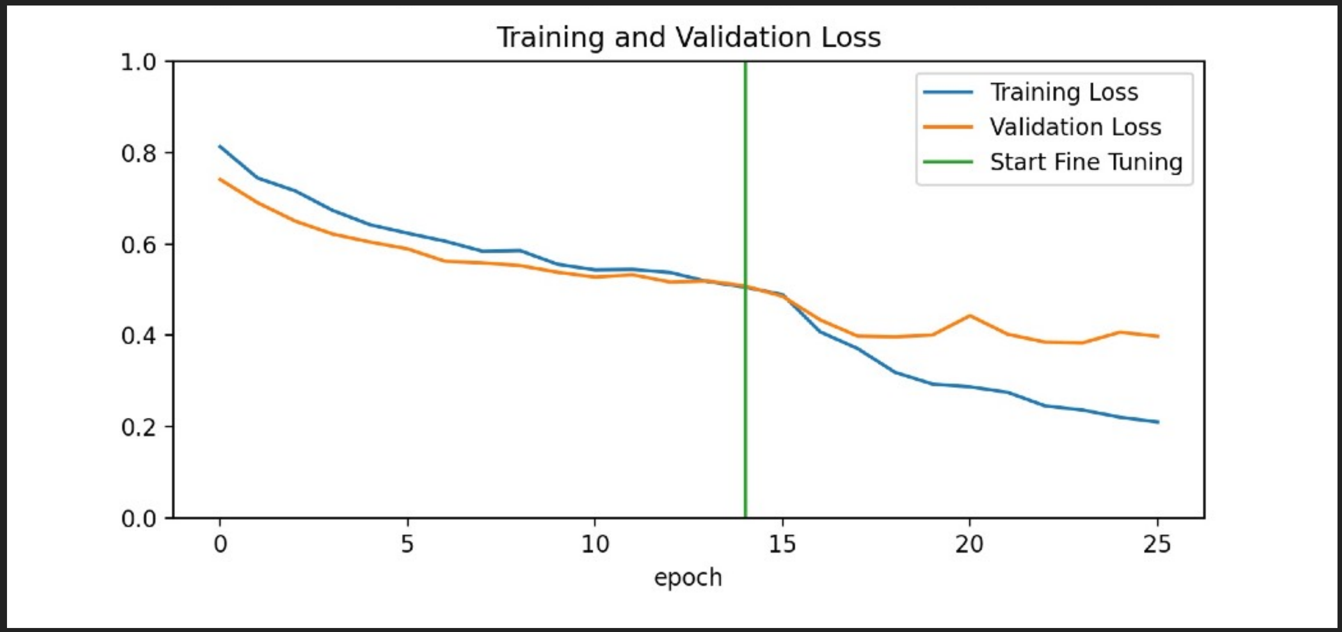


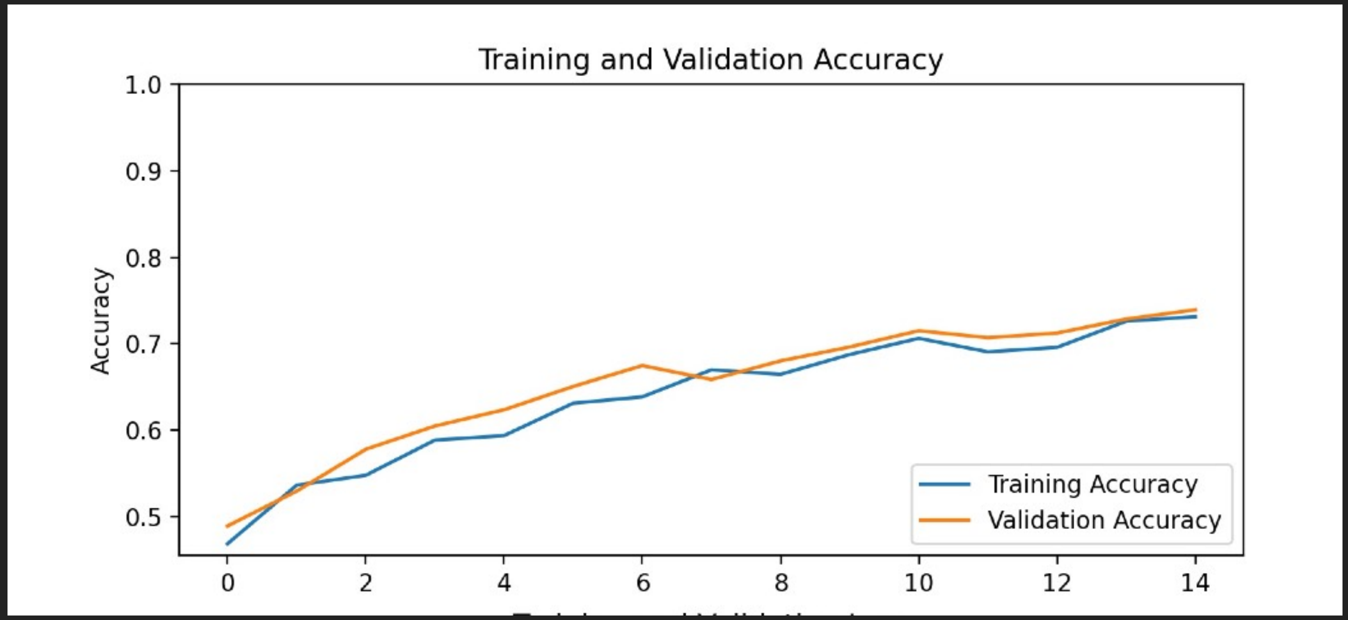


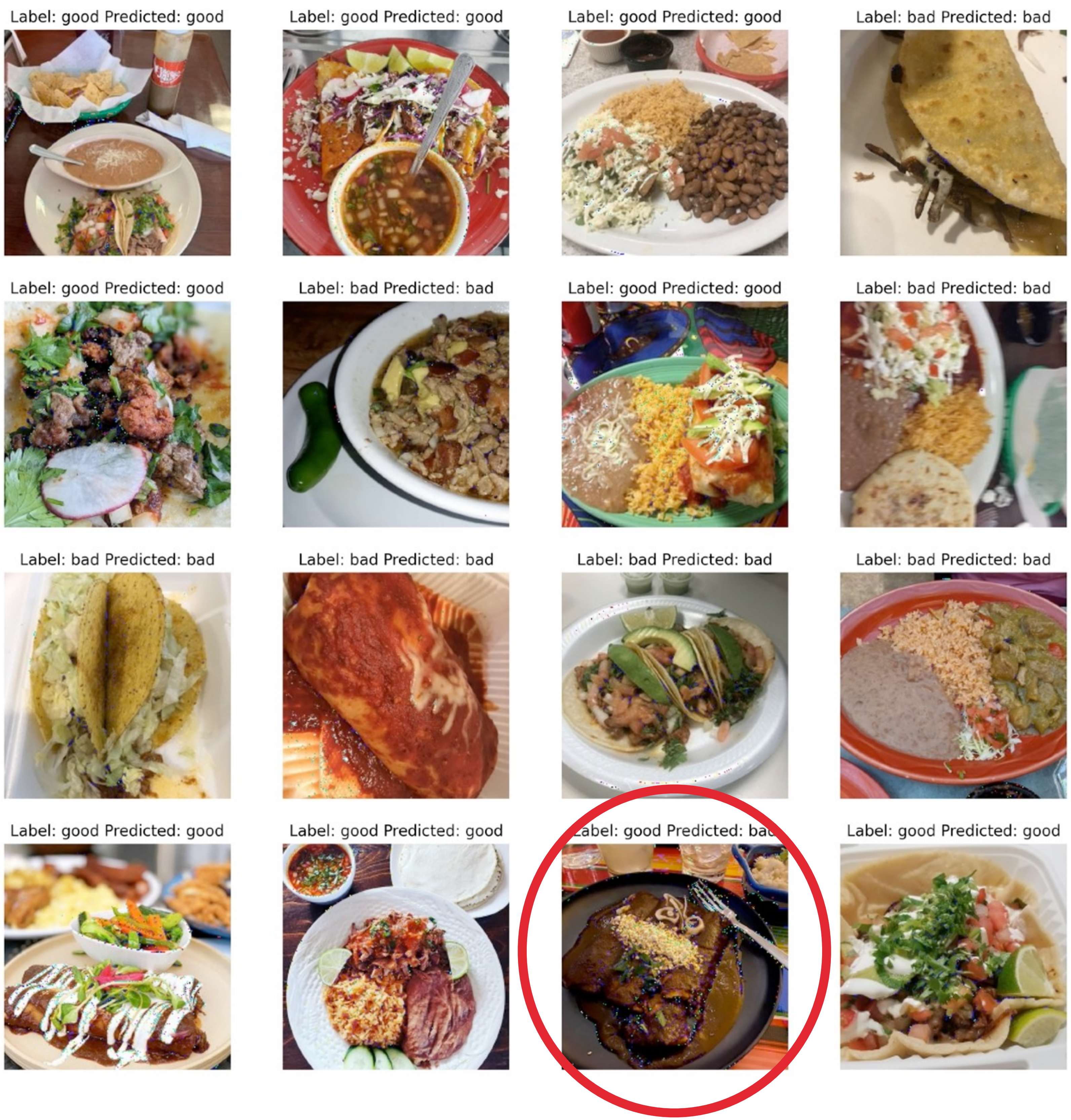
MODEL 4: ~83% ACC

~83% on Validation Data after 10 epochs

- A fine-tuning transfer learning model
- Unfreezes a few of the top layers from the MobileNet V2
- Lets you take advantage of basic features in lower part of pre-train, then get more specific for your data.






Label: good Predicted: good
Label: good Predicted: good
Label: good Predicted: good
Label: bad Predicted: bad
Label: good Predicted: good
Label: bad Predicted: bad
Label: good Predicted: good
Label: bad Predicted: bad
Label: bad Predicted: bad
Label: bad Predicted: bad
Label: bad Predicted: bad
Label: bad Predicted: bad
Label: good Predicted: good
Label: good Predicted: good
abel: good Predicted: ba
Label: good Predicted: good

CONCLUSIONS

CONCLUSIONS

- More difficult to evaluate subjective labels.
- Sometimes CNNs with transfer learning don't perform better than those without.
- CNNs: are like poker.
- Try limiting down the dataset to more specific shapes(e.g. sushi).
- Try a CNN w/ specific architecture for color patterns.

Source

RECOMMENDATIONS

RECOMMENDATIONS

- Review platforms with user-generated photo galleries should consider implementing AI-based photo-quality sorting.
- This idea has other applications beyond review platforms; many are already in production such as on this website: www.pickpik.com