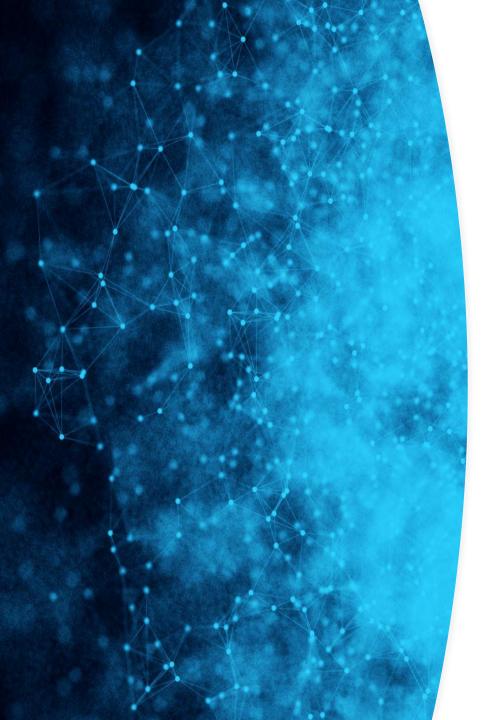


Objectives

- To build a Deep Learning Model that can accurately detect faces and predict face emotions.
- Understand if adding physical layer augmentation techniques to train a Deep Learning Model will help improve model performance, while reducing the number of pixels used.
- Compare the model results for various physical layer augmentation techniques and conclude which technique performs the best when predicting Face Emotions.



### Abstract

- We explored various physical layer augmentation techniques such as top-half mask, bottom-half mask, one-fourth mask on the Face Emotion Classification Dataset.
- We used a VGG-16 model architecture for Face Emotion Classification.
- We further used the following metrics to assess performance:

Accuracy

Precision

Recall

F1 Score



### Data Source

Took a subset of the "Face expression recognition dataset" by Jonathan Oheix on Kaggle. Consists of only grayscale (black-and-white) images.

Нарру	Neutral	Sad
8989 Image	6198 Images	6077 Images







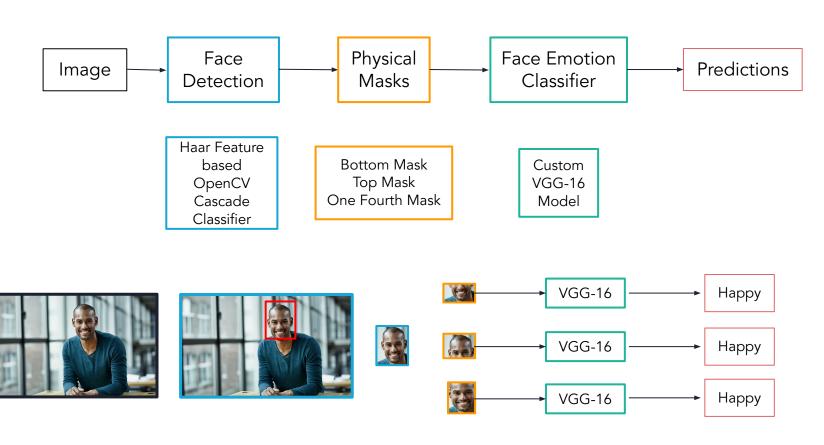


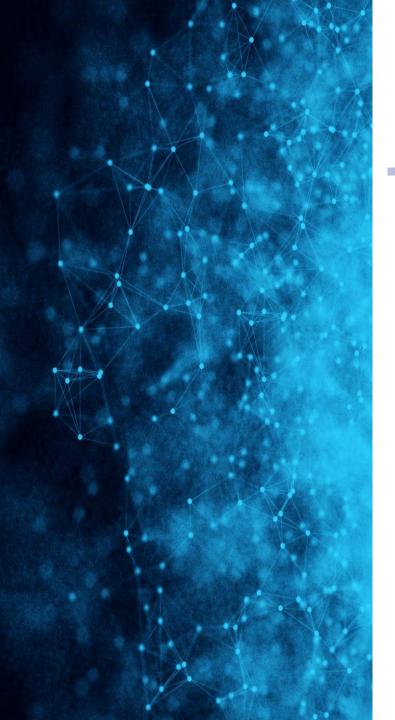
# Tackling Data Bias

- Ensured that there were at least 5000 images in training for each emotion
- Balanced proportion of males and females
- Various races present in the dataset
- Various facial views (front and side views)
- Balanced proportion of age groups



# Methodology





### Data Augmentation for Emotion Classification

Utilized a sharpness kernel to improve the model classification accuracy.

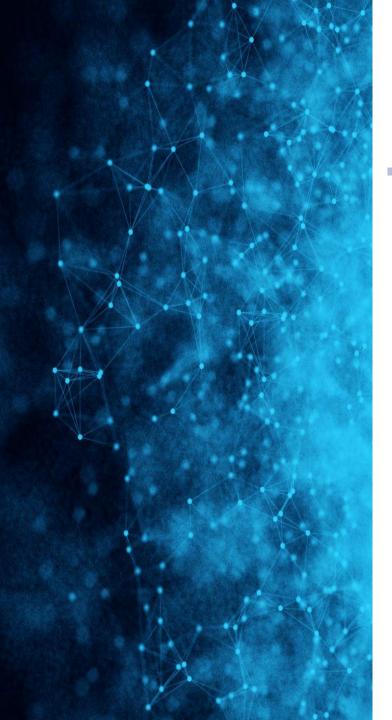
$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

Original Image

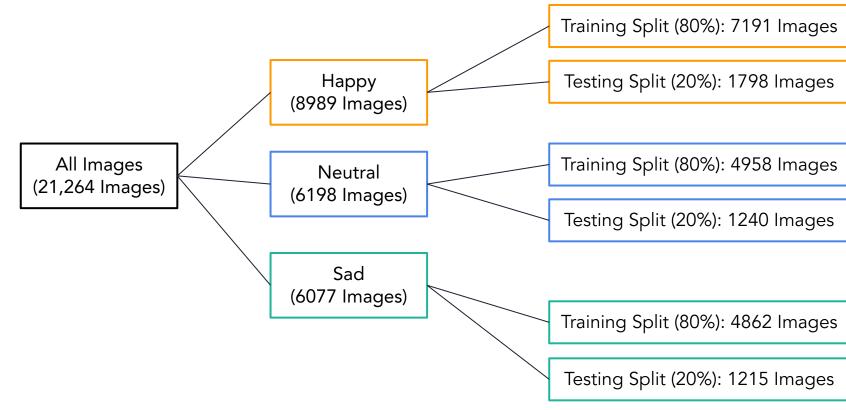


Sharpened Image



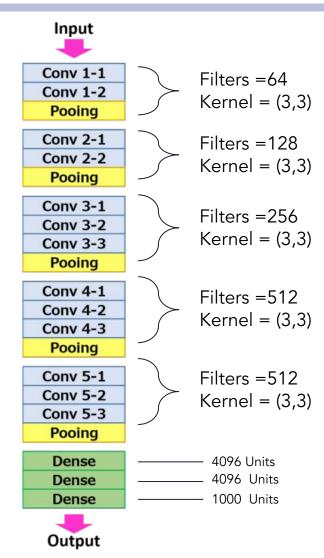


# Data Pipeline





### VGG -16 Model



Optimizer: Adam

Learning Rate: 0.0001

Loss: Sparse Categorical Cross

Entropy

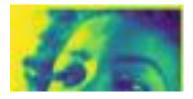
Batch Size: 64



Original Image







Bottom-Half Mask



One-Fourth Mask

# Hyperparameters We Experimented With

We decided to use a VGG-16 Model with the following hyperparameters:

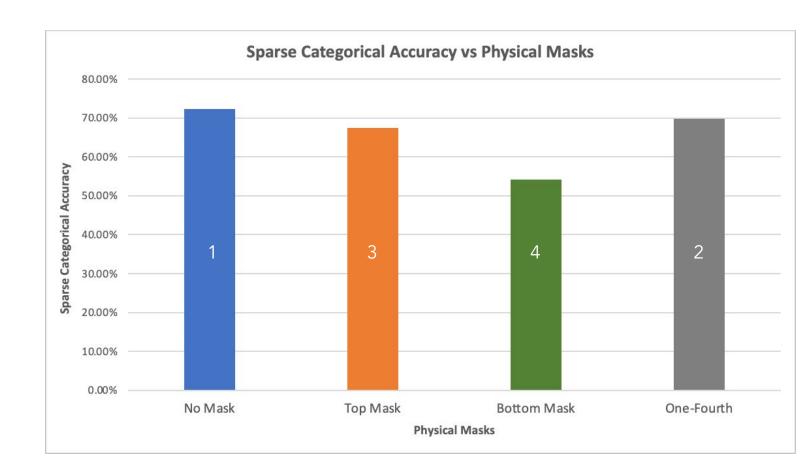
- Learning Rate: 1e-3, 1e-4, 1e-5
- L2 Regularization: 1e-4, 1e-3, 1e-5
- Dropout: 0.05, 0.5, 0.6, 0.7

For Physical Layer Augmentation Techniques, we implemented the following:

- Top-Half Mask
- Bottom-Half Mask
- One-Fourth Mask

### Results

	Validation Metrics	Overall
No Mask	Accuracy	72.31%
	F1 Score	72.29%
Top Mask	Accuracy	67.42%
	F1 Score	67.85%
Bottom	Accuracy	54.16%
Mask	F1 Score	54.40%
One-Fourth	Accuracy	69.76%
Mask	F1 Score	69.77%



### Results (cont'd): Precision & Recall

#### Precision

Precision	Нарру	Sad	Netural
No Mask	86%	61%	65%
Top Mask	85%	55%	58%
Bottom Mask	64%	54%	42%
One- Fourth	86%	56%	65%

#### Recall

Recall	Нарру	Sad	Netural
No Mask	84%	71%	56%
Top Mask	77%	60%	60%
Bottom Mask	61%	50%	48%
One- Fourth	81%	74%	50%

# Conclusion

- We can remove ½ pixels and still achieve near baseline accuracy.
- Each masked model performs the best when predicting the emotion Happy.
- As expected, the model performance indicates that the forehead is not extremely important while predicting face emotions.
- More importantly, the bottom half of the face is critical in predicting these facial emotions.



# Flask Web-App

### Home Page

Welcome to Face Emotion Detection Engine!!				
Please upload an image below to proceed!!				
Choose File No file chosen				
Submit				

### Step-1 Face Detection

#### **Step 1: Face Detection**

Please find below the original image, grayscale boxed image, and cropped image.

Click on the button below to proceed to Step 2



Step 2

#### Original Image



#### **Grayscale Boxed Image**



#### **Grayscale Cropped Image**



### Step-2 Emotion Detection

#### **Step 2: Emotion Detection**

Please find below the original image, top-half, bottom-half, three-fourths masked images, and the model classification! The model classifies between HAPPY, SAD, and NEUTRAL

Try a new image!



Overall Classification is as follows:

Majority (Ensemble) Classification:

#### Happy

Best Model (Three-Fourths Model) Classification:

#### Happy

### Grayscale Cropped Image



Happy: 1.0 Sad: 0.0 Neutral: 0.0

#### Top-Half Masked Image



Happy: 1.0 Sad: 0.0 Neutral: 0.0

#### Bottom-Half Masked Image



Happy: 1.0 Sad: 0.0 Neutral: 0.0

### Three-Fourths Masked Image



Happy: 1.0 Sad: 0.0 Neutral: 0.0



# Step-2 (cont'd) Emotion Detection Classification

#### Best-Model Classification

One-Fourth Mask Model

#### Majority Ensemble Voting Classification

- Pools the classification results from baseline (no-mask), top-half mask, bottom-mask, and one-fourth mask models.
- Votes on the majority classification, to identify winning label.
- In case of tie, the best model classification is used as a tiebreaker.



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- 1. Pei, Zhao, et al. "(PDF) Face Recognition via Deep Learning Using Data Augmentation Based on Orthogonal Experiments." *ResearchGate*, https://www.researchgate.net/publication/336061375\_Face\_Recognition\_via\_Deep\_Learning\_Using\_Data\_Augmentation\_Based\_on\_Orthogonal\_Experiments.
- 2. Li, Jessica. "Labelled Faces in the Wild (LFW) Dataset." *Kaggle*, 17 May 2018, https://www.kaggle.com/jessicali9530/lfw-dataset.
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- 5. Porcu, Simone, et al. Evaluation of Data Augmentation Techniques for Facial ...

https://www.researchgate.net/publication/345940392\_Evaluation\_of\_Dat a\_Augmentation\_Techniques\_for\_Facial\_Expression\_Recognition\_Syst ems.

