



# CAPSTONE PROJECT

## FACIAL EMOTION DETECTION – DEEP LEARNING



# BACKGROUND

- Facial expressions plays a significant role
  - 55% of emotional exchanges occur through facial expressions
  - Communicate and understand emotions
- Facial emotion detect helps create more emotionally intelligent machines
  - Improve human-machine interactions in a variety of settings
- Create a deep learning model that can classify multiple classes of facial expressions
  - Happy, Sad, Neutral, Surprise



# BACKGROUND

- Application are mostly used in
  - Healthcare
  - Education
  - Marketing
  - Entertainment



# INTRODUCTION

- The most effective algorithms and techniques for recognizing and classifying emotions
- Address bias and fairness in facial emotion detection
- Improve the accuracy and performance of facial emotion detection system



# SOLUTION APPROACH

Data  
Exploration

Build  
Model  
And  
Evaluate

Final Model  
Solution



# DATA EXPLORATION

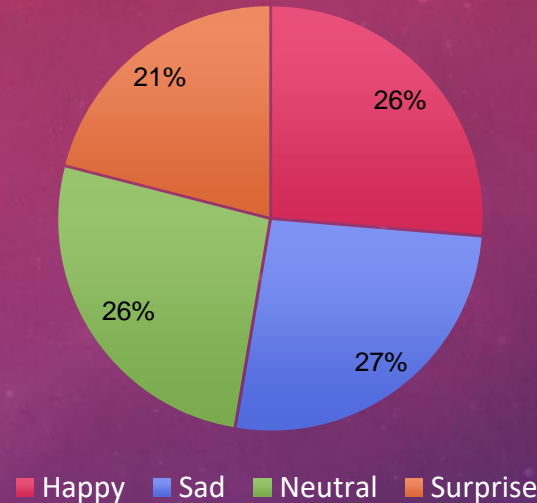
- Key patterns of the facial expressions
  - Mouthing, Eyebrows, Cheek
- Data distribution
  - Affect the performance of the model
- EDA
  - Image statistics



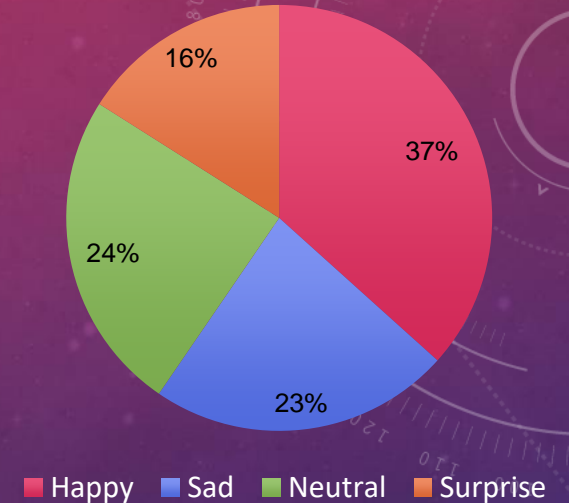
# DATA EXPLORATION

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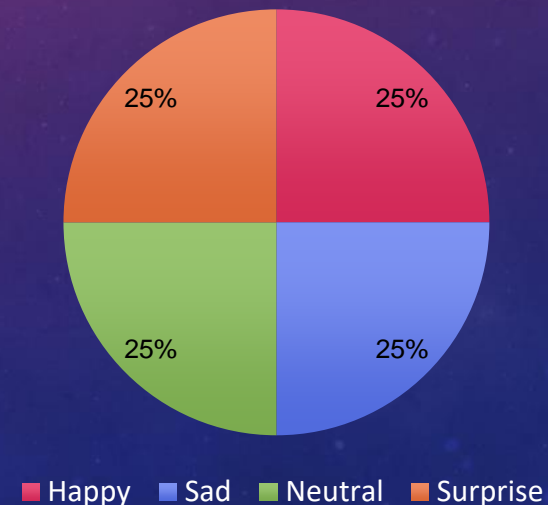
## Training data



## Validation data



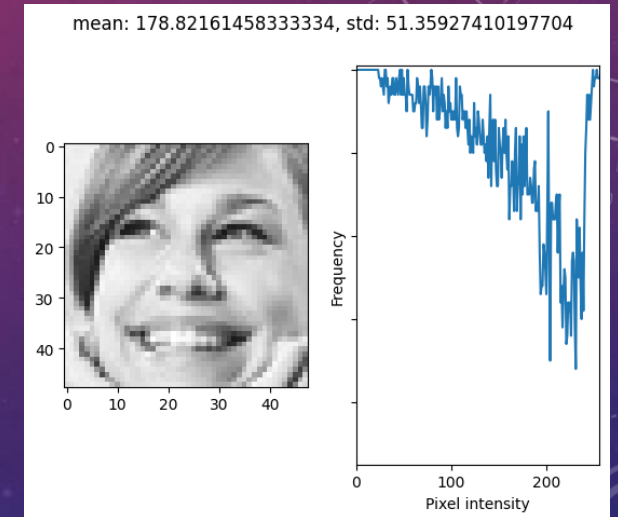
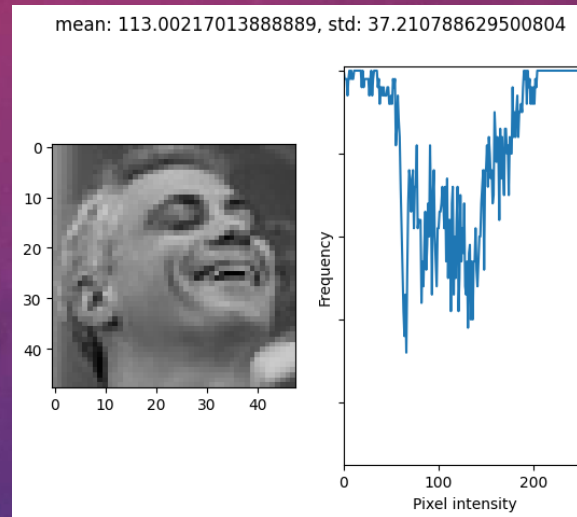
## Testing data





# DATA EXPLORATION

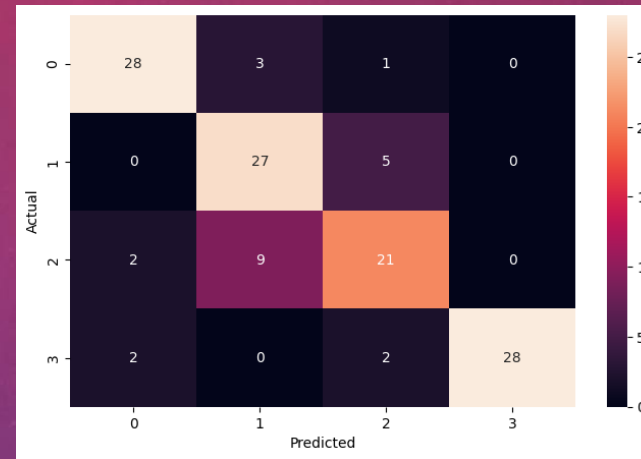
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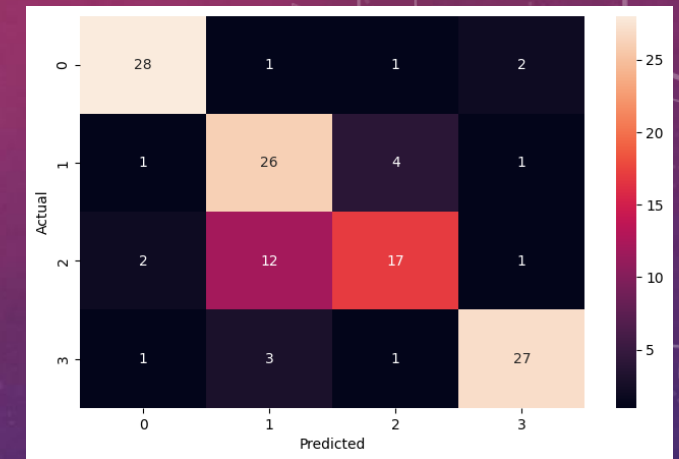


# BUILD MODEL - TRANSFER LEARNING

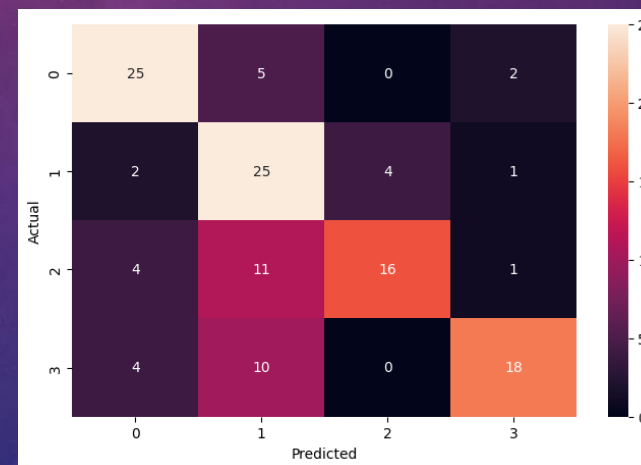
- VGG16, ResNet v2, Efficient Net
- VGG16 Accuracy
  - Training: 78.75%
  - Validation: 77.6%
  - Testing: 81%
  - F1-score: 0.88, 0.76, 0.69, 0.93
- ResNet v2 Accuracy
  - Training: 77.17%
  - Validation: 76.01%
  - Testing: 77%
  - F1-score: 0.88, 0.70, 0.62, 0.86
- Efficient Net
  - Training: 74.71%
  - Validation: 69.24%
  - Testing: 66%
  - F1- score: 0.75, 0.60, 0.62, 0.67



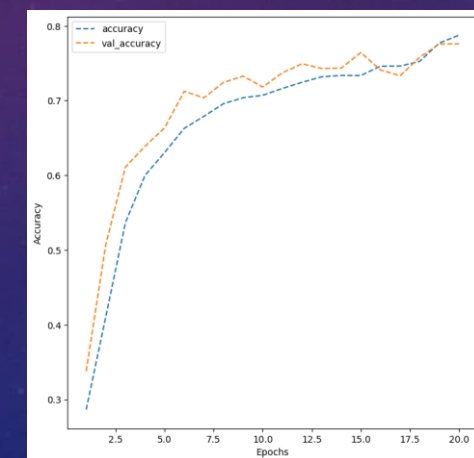
VGG16



ResNet v2



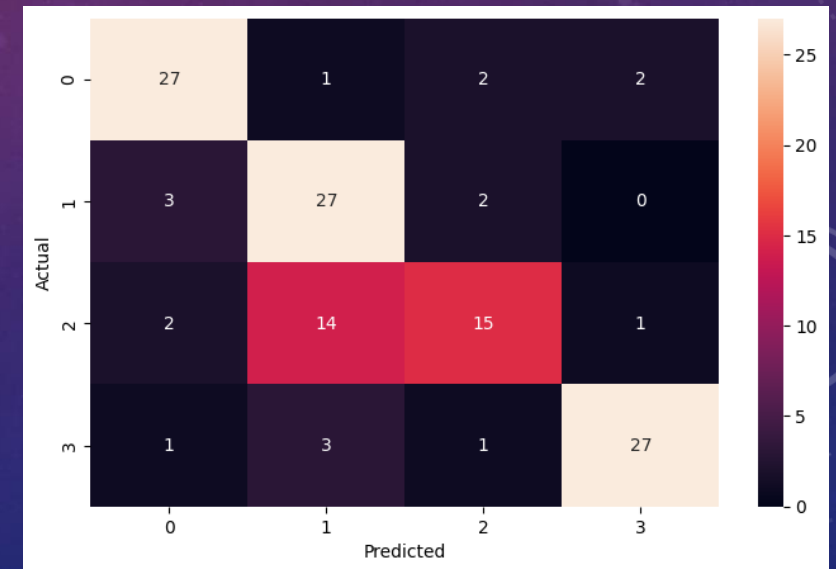
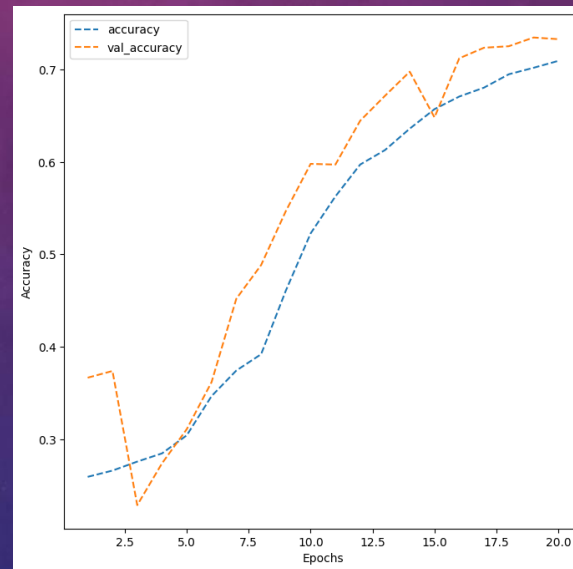
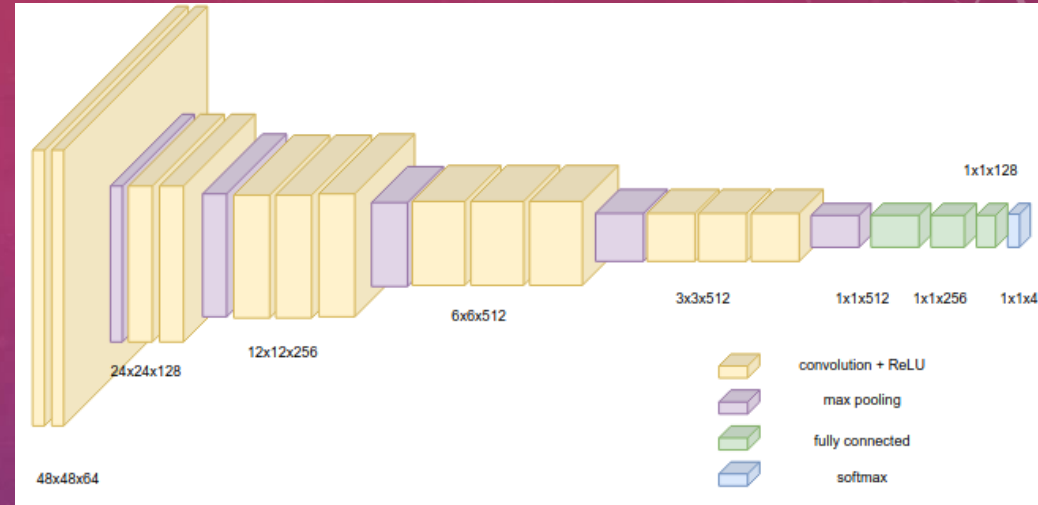
Efficient Net



VGG16 accuracy

# BUILD MODEL - CUSTOM BUILT MODEL

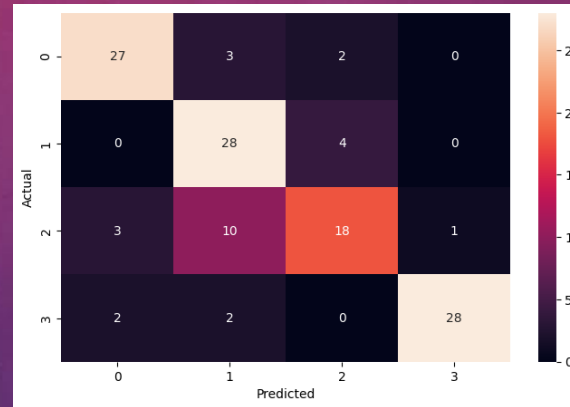
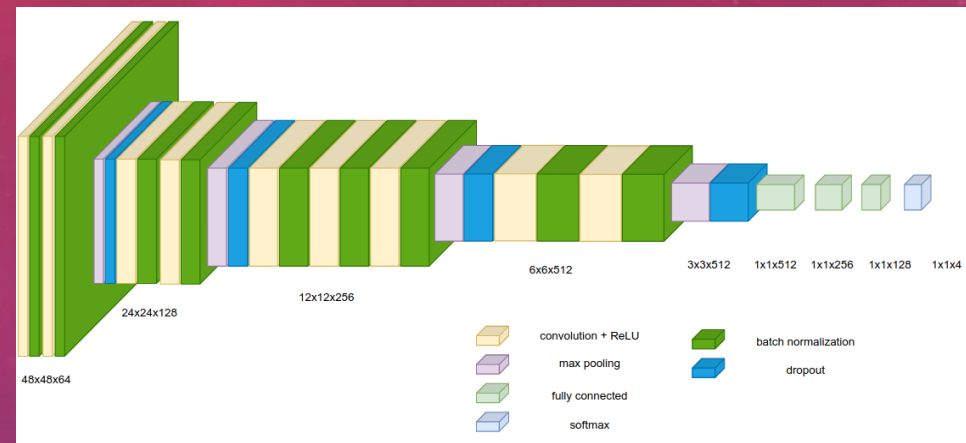
- 5-block CNN Model
- Accuracy
  - Training: 70.93%
  - Validation: 73.28%
  - Testing: 75%
  - F1-score: 0.83, 0.70, 0.58, 0.87



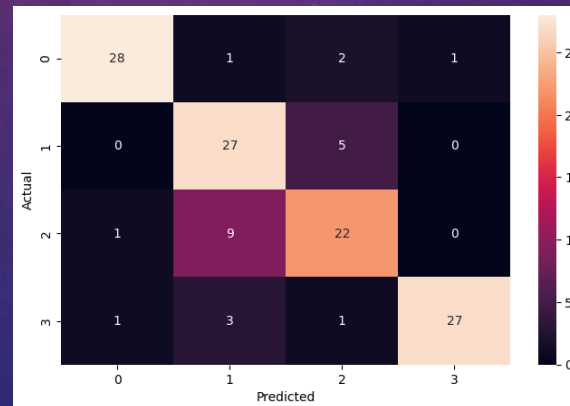


# BUILD MODEL - CUSTOM BUILT MODEL

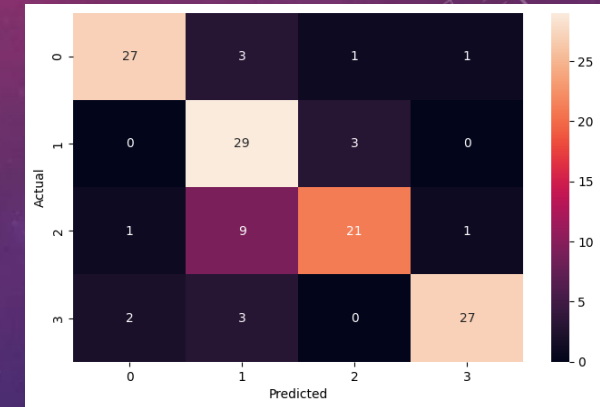
- 4-block CNN Model with batch normalization and dropout
- Accuracy
  - Without class weight: 79%
    - F1-score: 0.84, 0.75, 0.64, 0.92
  - Class 'sad' and 'neutral' weight 3 : 81%
    - F1-score: 0.87, 0.76, 0.74, 0.89
  - Class 'sad' and 'neutral' weight 3.5: 81%
    - F1-score: 0.90, 0.75, 0.71, 0.90
  - Class 'sad' and 'neutral' weight 4: 80%
    - F1-score: 0.89, 0.74, 0.74, 0.84



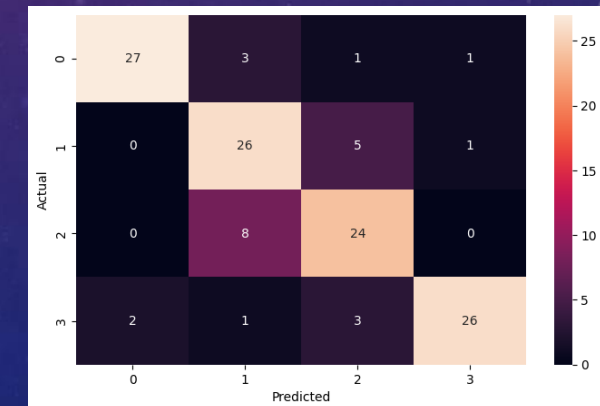
Without class weight



'sad' and 'neutral' weight: 3.5



'sad' and 'neutral' weight: 3



'sad' and 'neutral' weight: 4

# SUMMARY

- On small dataset and domain-specific tasks, pretrained models may perform worse than custom built model
- Dropout and batch normalization can help adjust model overfitting or underfitting
- Increasing epochs in custom model can improve accuracy
- Training with class weights helps to classify specific classes



# PROPOSED SOLUTION

- Apply data cleaning
- Increase dataset
- Ensemble learning



# FUTURE DISCUSSION

**Real time  
detection**

**Application**



The background is a gradient from deep blue at the bottom to a vibrant magenta at the top. It is decorated with several white circular elements: a large scale on the left with degree markings from 140 to 260, and several smaller concentric circles with arrows indicating clockwise or counter-clockwise movement. The text "THANK YOU!" is positioned in the lower right area in a clean, white, sans-serif typeface.

THANK YOU!

# REFERENCE

- [1] <https://content.time.com/time/business/article/0,8599,1954643,00.html>
- [2] <https://www.kaspersky.com/resource-center/definitions/biometrics>
- [3] <https://www.thalesgroup.com/en/markets/digital-identity-and-security/government/biometrics/facial-recognition>
- [4] John Chris T. Kwong, Felan Carlo C. Garcia, P. Abu, R. Reyes  
Emotion Recognition via Facial Expression: Utilization of Numerous Feature Descriptors in Different Machine Learning Algorithms, 2018