# Real-Time Emotion Recognition Detection in Education

Xi (Ciel) Zhao

CONTENTS

01 Introduction

02 Processing/EDA

Fitting Model & Performance Tuning

04 Transfer Learning

05 Conclusion & Application

# Introduction

#### Goal

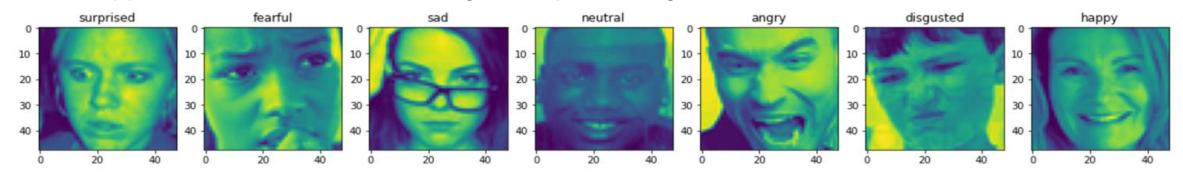
By using Real-Time Emotion Recognition detection to help schools and teachers understand students' emotion towards to the course.



#### Introduction

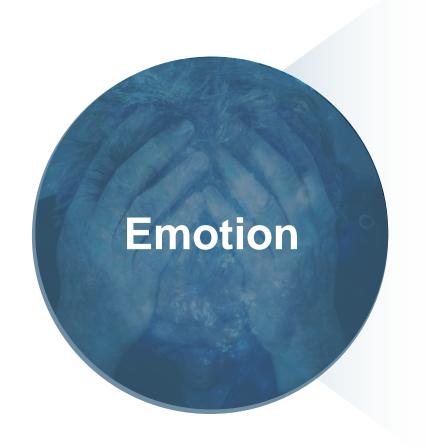
#### **Emotion Detection Dataset - Kaggle**

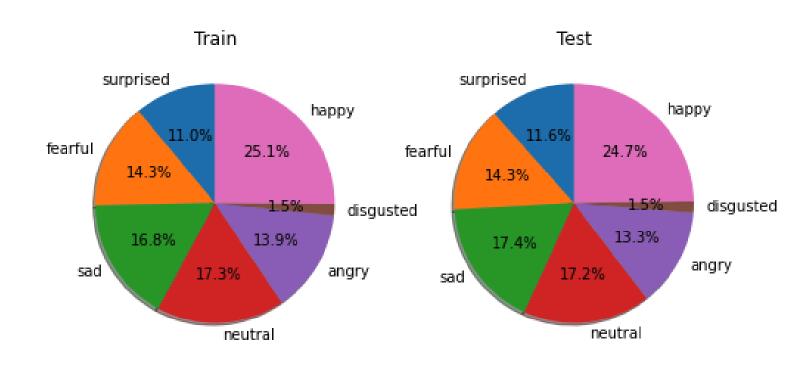
- The dataset contain 35,685 examples of 48x48 pixel gray scale images of faces.
- The dataset already divided into train and test dataset.
- Train dataset: 28709 Test dataset: 6976
- There are seven categories based on facial emotion images
- Happiness, Neutral, Sadness, Anger, Surprise, Disgust, Fear.



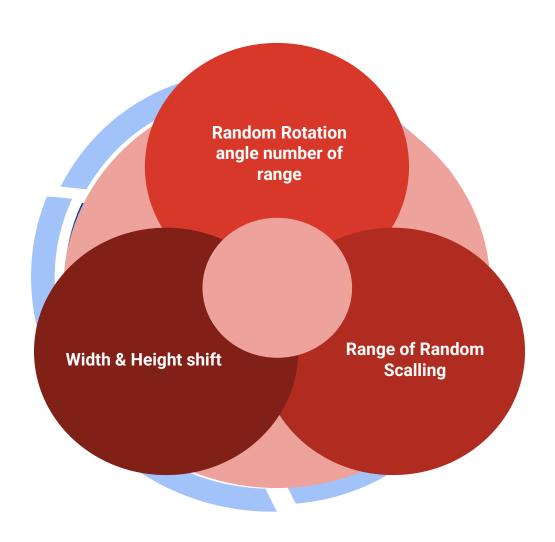
# Process/EDA

## Distribution of Seven Categories





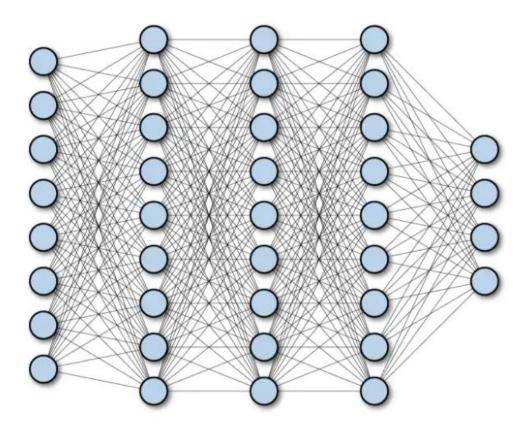
## Preparation for next step



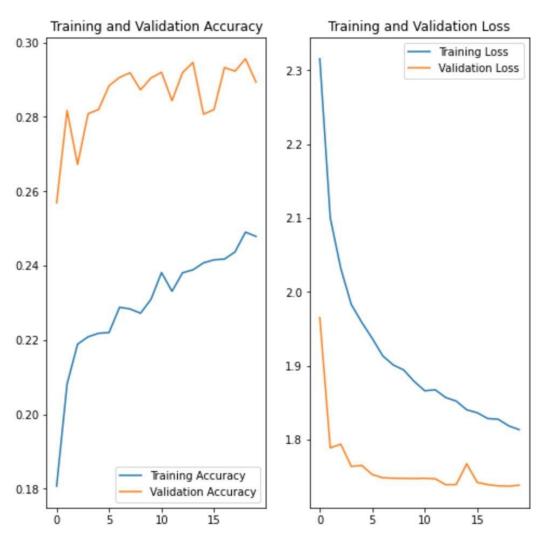
# Fitting Model & Performance Tuning

### Fully Connected(dense) Networks

A fully connected neural network consists of a series of fully connected layers that connect every neuron in one layer to every neuron in the other layer.



## Fully Connected(dense) networks



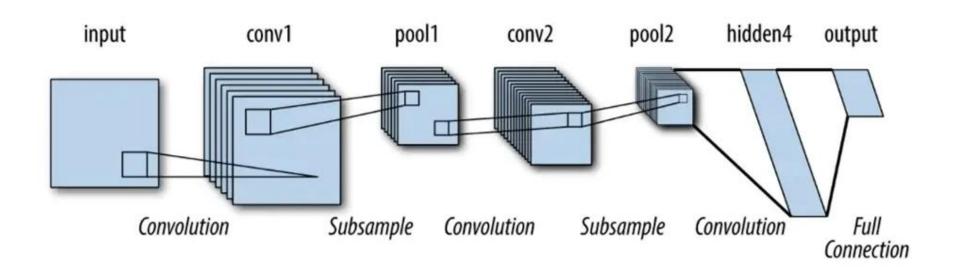
Training accuracy: 0.2479

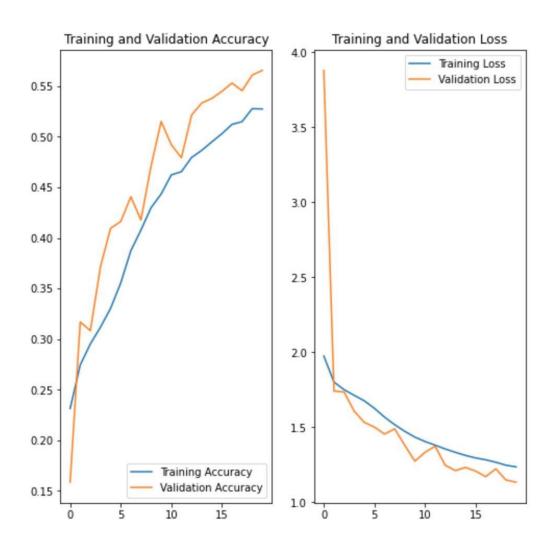
Validation accuracy: 0.2894

Training loss: 1.8134

CNN architectures make the explicit assumption that the inputs are images, which allows encoding certain properties into the model architecture.

A simple CNN is a sequence of layers, and every layer of a CNN transforms one volume of activations to another through a differentiable function. Three main types of layers are used to build CNN architecture: Convolutional Layer, Pooling Layer, and Fully-Connected Layer.





Training accuracy: 0.5274

Validation accuracy: 0.5655

Training loss: 1.2370

Validation loss: 1.1351

Test accuracy:0.5655

Test loss:1.1351

#### Try various network architectures——L1

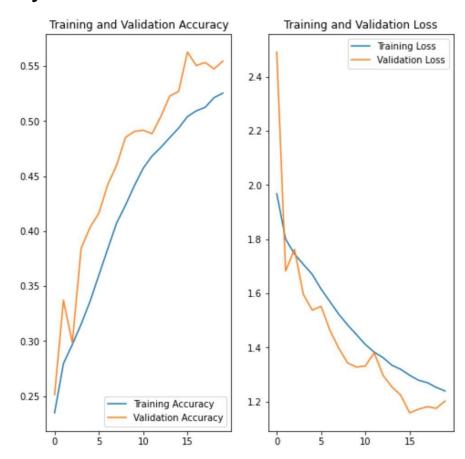


Training accuracy: 0.5292

Validation accuracy: 0.5666

Training loss: 1.2376

#### Try various network architectures—L2

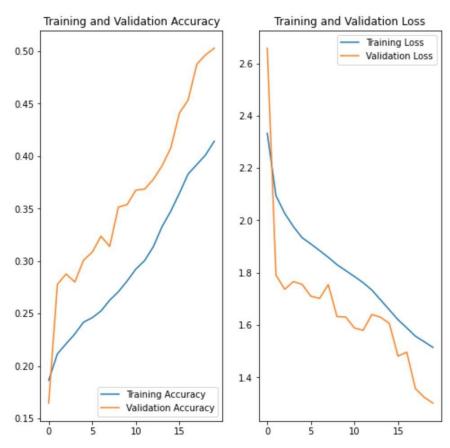


Training accuracy: 0.5254

Validation accuracy: 0.5545

Training loss: 1.2387

Try various network architectures—add dropouts



Training accuracy: 0.4141

Validation accuracy: 0.5026

Training loss: 1.5146

# Transfer Learning

#### MobileNetV2

MobileNetV2 is a convolutional neural network (CNN) designed for efficient ondevice mobile and embedded vision applications.

The MobileNetV2 architecture is based on an inverted residual structure where the input and output of the residual block are thin bottleneck layers opposite to traditional residual models which use expanded representations in the input. MobileNetV2 uses lightweight depthwise convolutions to filter features in the intermediate expansion layer.

#### MobileNetV2



Training accuracy: 0.7068

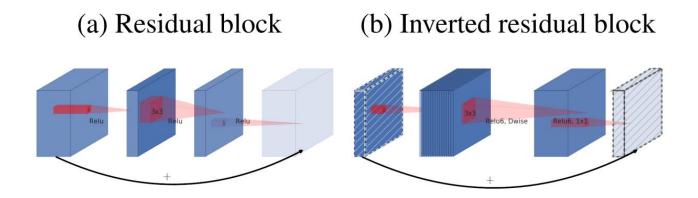
Validation accuracy: 0.4646

Training loss: 0.7896

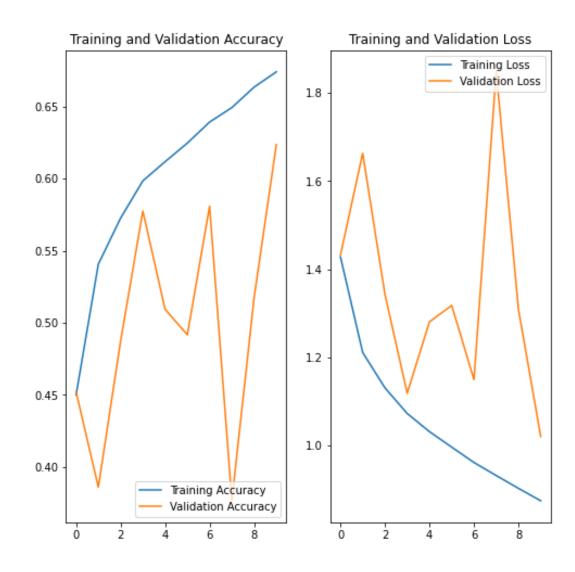
#### Resnet50

ResNet50 is a 50-layer deep CNN, with a large number of parameters, that has achieved very good performance on a variety of image classification and object detection tasks.

One of the key features of ResNet50 is the use of residual connections. This helps to alleviate the problem of vanishing gradients, which can occur in very deep networks, and allows ResNet50 to learn more effectively.



#### Resnet50



Training accuracy: 0.6740

Validation accuracy: 0.6236

Training loss: 0.8741

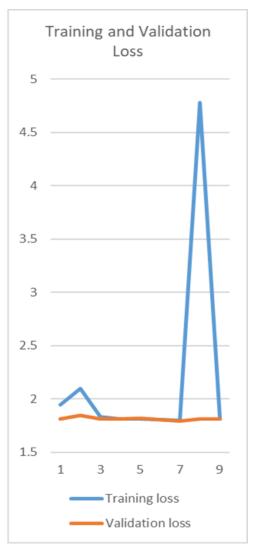
#### VGG16

VGG16 is a 16-layer CNN that has been trained on the ImageNet dataset, which contains over 1.2 million images and 1000 classes.

VGG16 consists of 13 convolutional layers and 3 fully-connected layers, which allows it to learn rich and complex features from the input images. It also uses a simple and uniform architecture, with all convolutional layers having a kernel size of 3x3 and a stride of 1, which helps to reduce the number of model parameters and improve the network's ability to generalize.

#### VGG16





Training accuracy: 0.2513

Validation accuracy: 0.2471

Training loss: 1.8101

# 5 Conclusion

## Summary

	CNN	CNN with L1	CNN with L2	CNN with Dropout	MobileNetV2	Resnet50	VGG16
Training Accuracy	0.5274	0.5292	0.5254	0.4141	0.7068	0.6740	0.2513
Validation Accuracy	0.5655	0.5666	0.5545	0.5026	0.4646	0.6236	0.2471

#### Issues

- 1. Large dataset —> AutoDL
- 2. Most of images are white poeple
- 3. How to improve accuracy

Add more hidden layers or units

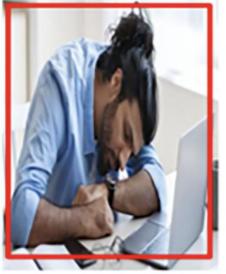
Preprocess the data

Use a larger training dataset

Fine-tune the model's hyperparameters

## **Application**





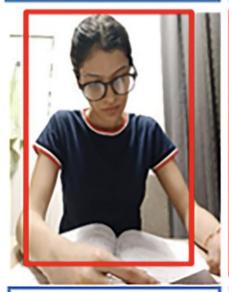


Anticipation

Sleeping

Happiness

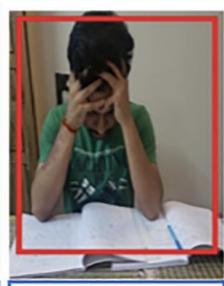
**Online Learning** 



Peace



Annoyance



**Frustration** 



#### Reference:

- Putra, W. B., & Arifin, F. (2019). Real-time emotion recognition system to monitor student's mood in a classroom. *Journal of Physics: Conference Series*, 1413(1), 012021. https://doi.org/10.1088/1742-6596/1413/1/012021
- 2. Ares. (2020, December 11). *Emotion detection*. Kaggle. Retrieved December 20, 2022, from <a href="https://www.kaggle.com/datasets/ananthu017/emotion-detection-fer">https://www.kaggle.com/datasets/ananthu017/emotion-detection-fer</a>
- 3. Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., & Chen, L. C. (2018). Mobilenetv2: Inverted residuals and linear bottlenecks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4510-4520).
- 4. Hollemans, M. (no date) MobileNet version 2, Mobilenet version 2. Available at: https://machinethink.net/blog/mobilenet-v2/ (Accessed: December 20, 2022).
- 5. Gupta, S., Kumar, P., & Tekchandani, R. K. (2022, September 9). Facial emotion recognition based real-time learner engagement detection system in online learning context using deep learning models -multimedia tools and applications. SpringerLink. Retrieved December 20, 2022, from https://link.springer.com/article/10.1007/s11042-022-13558-9
- 6. Ramsundar, B., & Zadeh, R. B. (2018). TensorFlow for deep learning: from linear regression to reinforcement learning. " O'Reilly Media, Inc.".