



THE UNIVERSITY OF TEXAS AT EL PASO

**ML Project – Team 2:
Face Recognition using
Convolutional Neural Networks**

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Overview

- **Problem Statement:** Background and Research Problem
- **Data:** Data Prep and Training
- **Methodology:** Architecture, Training
- **Features:** Highlights and Problems
- **Results:** Mapping and evaluation
- **Summary:** Review, Impact, Future Work

Problem Statement: Background

- Face recognition purpose:
- Identification or verification of individuals
- Applications:
- surveillance, access control, authentication, and personalized services



Why ML?

- Traditional methods of face recognition often rely on handcrafted features
- CNN:
 - learn and extract complex patterns from vast amounts of data
 - excel in feature learning and abstraction,

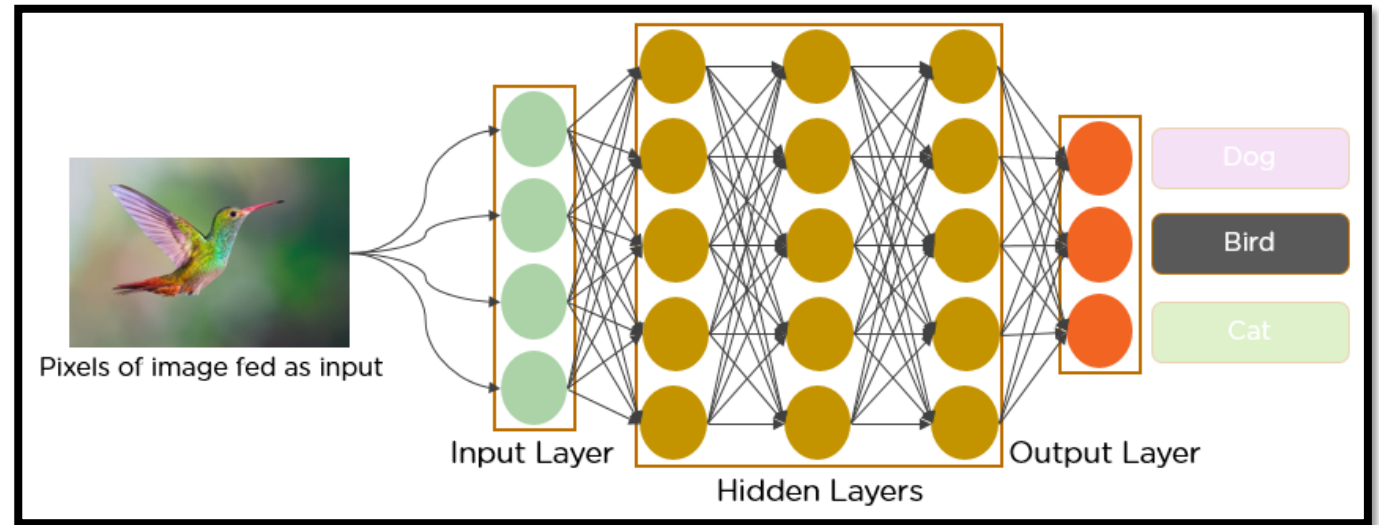


Fig. 3: CNN Process Example

Data Preparation

	pixel_0	pixel_1	pixel_2	pixel_3	pixel_4	pixel_5	pixel_6	pixel_7	pixel_8	pixel_9	...
0	117	97	84	72	66	60	67	72	71	62	...
1	254	253	254	254	254	255	253	249	214	207	...
2	252	255	255	252	255	254	251	237	178	99	...
3	253	254	233	244	254	254	253	254	253	253	...
4	247	247	247	246	245	245	243	241	237	227	...

Fig. 2: Header Data Set

```
import os
import pandas as pd
from tqdm import tqdm
import numpy as np
from PIL import Image

# Define folder names
folders = ['derek1000']

# Define path to the folder containing subfolders
main_path = '/Users/magarciafer/Desktop/ml/Cnn/Dataset_Creation/Datasets'

# Define output CSV filename
filename = 'derek100test.csv'

# Target dimensions for the images
dim = (100, 100)

cls = 0 # Initialize to 0, which will be incremented inside the loop

# Create an empty DataFrame
df = pd.DataFrame(columns=[f'pixel_{i}' for i in range(dim[0] * dim[1])] + ['class'])

# Find the minimum number of images in any folder
min_images = float('inf')
for folder in folders:
    folder_path = os.path.join(main_path, folder)
    files = os.listdir(folder_path)
    if len(files) < min_images:
        min_images = len(files)

# Process images ensuring equal number per class
for folder in folders:
    cls += 1 # Increment class label for each folder
    folder_path = os.path.join(main_path, folder)
    files = os.listdir(folder_path)
    # Use min_images to limit the number of processed files
    for i in tqdm(range(min_images)):
        img = Image.open(os.path.join(folder_path, files[i])).convert('L') # Convert image to grayscale
        img_resized = img.resize(dim) # Resize image to 100x100
        img_array = np.array(img_resized).flatten() # Convert image to array and flatten
        df.loc[len(df)] = list(img_array) + [cls] # Append flattened image data and class to the DataFrame

# Set the index to start from 0
df.index.name = ''

# Save DataFrame to CSV
df.to_csv(filename, index=True)
print('Task Completed')
```

Fig. 3: Script Convert to CSV

```
# Importing Modules guu
import cv2
import numpy as np
import os
from tqdm import tqdm

#marco was here
def Crete_Folder_Images(name, directory, tn):
    # Creating directory in the file
    if not os.path.exists(directory):
        os.makedirs(directory)
    else:
        print('DIRECTORY with name %s EXIST'%name)
    # Opening video mode with frontal face detector
    faceDetect=cv2.CascadeClassifier(cv2.data.haarcascades + "haarcascade_frontalface_default.xml") #cv2.Cascade
    cam=cv2.VideoCapture(0)
    size =(100, 100)
    for i in tqdm(range(1, 1+ tn)):
        ret,img=cam.read()
        gray=cv2.cvtColor(img,cv2.COLOR_BGR2GRAY) #for GRAY SCALE IMAGES
        faces=faceDetect.detectMultiScale(gray,1.3,5)
        # faces=faceDetect.detectMultiScale(img,1.3,5) # FOR COLOR IMAGES
        for (x,y,w,h) in faces:
            res = cv2.resize(gray[y:y+h,x:x+w], size, interpolation = cv2.INTER_AREA)
            cv2.imwrite('Datasets/'+str(name)+'_'+str(name)+'_'+str(i)+'.jpg', res) #for GRAY SCALE IMAGES
            # cv2.imwrite(directory+'/'+str(name)+'_'+str(sn)+'.jpg'
            # ,img[y:y+h,x:x+w]) # FOR COLOR IMAGES
            cv2.rectangle(img,(x,y),(x+w,y+h),(0,0,255),2)
            cv2.waitKey(200)
        cv2.imshow('Dataset Creator',img)
        cv2.waitKey(1)
    cam.release()
    cv2.destroyAllWindows()
    print('TASK COMPLETED')

# Taking inputs

name=input('\nEnter your name: ')

directory='Datasets/'+name
tn= int(input('Enter no.of Images to be taken: '))
Crete_Folder_Images(name, directory, tn)
```

Fig. 4: Script Photo Automation

- Run a script to take 2,500 photos per class (Member team)
- Pictures are resized to a standard 100 * 100 pixels
- Labels are one-hot encoded into a csv
- Data is split into training and testing sets

Training Process

Statistics of the Dataset

- Has a leader dynamic
- count 6796.000000
- mean 2.500000
- std 1.118116
- min 1.000000
- 25% 1.750000
- 50% 2.500000
- 75% 3.250000
- max 4.000000
- Name: class, dtype: float64

Class Labels: [1, 2, 3, 4]

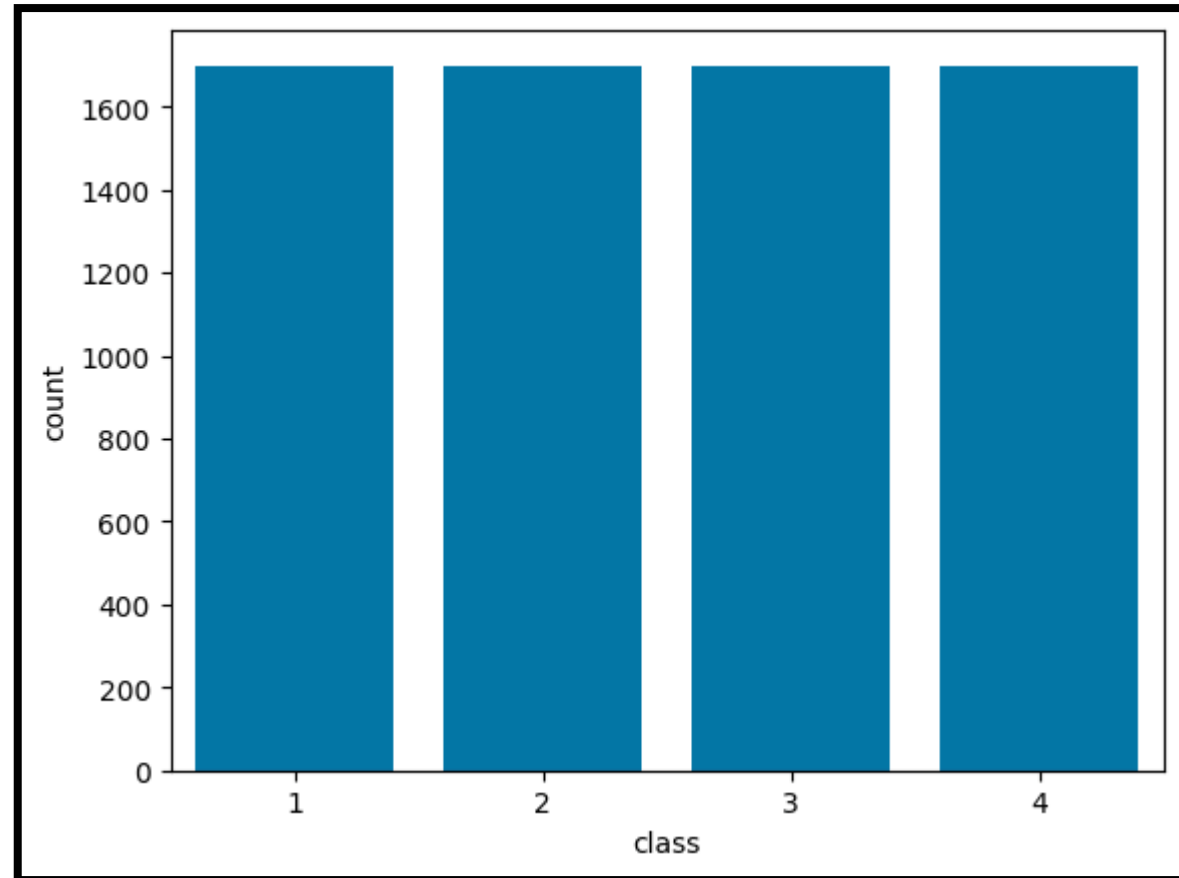


Fig. 5: Class Photos

Clusters

Some clusters are linearly separable in certain dimensions

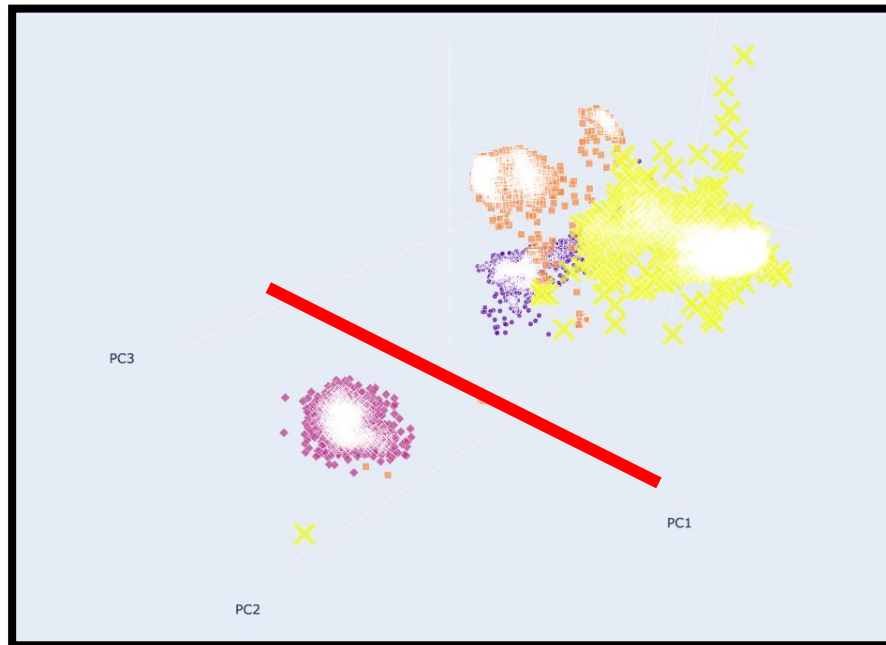
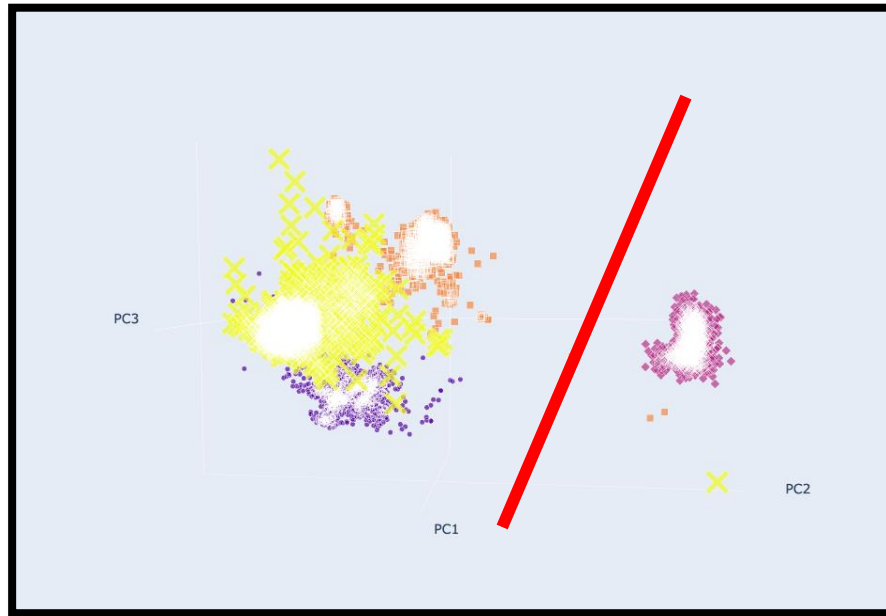
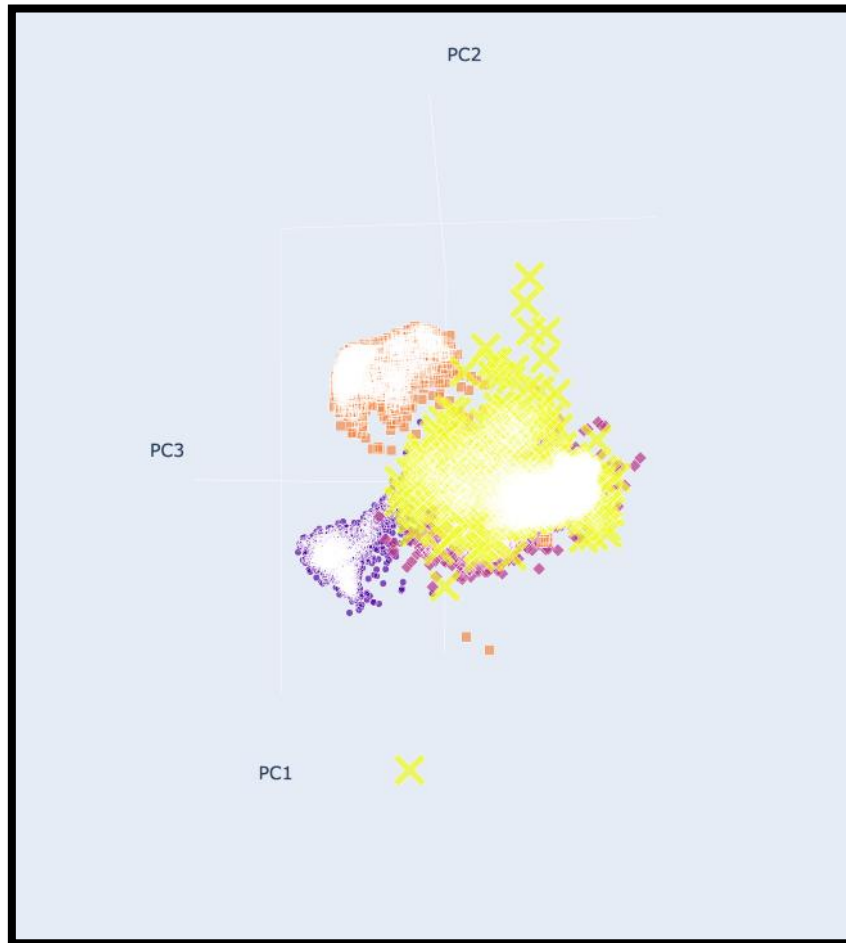


Fig. 6,7,8: Cluster of 4 classes

Model Proposed

```

model = Sequential(name = model_name)

model.add(Conv2D(64, kernel_size=3, activation='relu', input_shape=(100, 100, 1)))
model.add(BatchNormalization()) #-----
model.add(Conv2D(64, kernel_size=3, activation='relu'))
model.add(BatchNormalization()) #-----
model.add(Conv2D(64, kernel_size=5, padding='same', activation='relu'))
model.add(BatchNormalization()) #-----
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.2)) #-----

model.add(Conv2D(128, kernel_size=3, activation='relu'))
model.add(BatchNormalization())
model.add(Conv2D(128, kernel_size=3, activation='relu'))
model.add(BatchNormalization())
model.add(Conv2D(128, kernel_size=5, padding='same', activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.2))

model.add(Conv2D(256, kernel_size=3, activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.2))

model.add(Flatten())
model.add(Dense(256))
model.add(BatchNormalization())
model.add(Dense(128))
model.add(BatchNormalization())
model.add(Dense(5, activation='softmax'))

model.summary()

```

Fig. 9: Script Photo Automation

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 98, 98, 64)	640
batch_normalization (Batch Normalization)	(None, 98, 98, 64)	256
conv2d_1 (Conv2D)	(None, 96, 96, 64)	36928
batch_normalization_1 (Batch Normalization)	(None, 96, 96, 64)	256
conv2d_2 (Conv2D)	(None, 96, 96, 64)	102464
batch_normalization_2 (Batch Normalization)	(None, 96, 96, 64)	256
max_pooling2d (MaxPooling2D)	(None, 48, 48, 64)	0
dropout (Dropout)	(None, 48, 48, 64)	0
conv2d_3 (Conv2D)	(None, 46, 46, 128)	73856
batch_normalization_3 (Batch Normalization)	(None, 46, 46, 128)	512
conv2d_4 (Conv2D)	(None, 44, 44, 128)	147584
batch_normalization_4 (Batch Normalization)	(None, 44, 44, 128)	512
conv2d_5 (Conv2D)	(None, 44, 44, 128)	409728
batch_normalization_5 (Batch Normalization)	(None, 44, 44, 128)	512
max_pooling2d_1 (MaxPooling2D)	(None, 22, 22, 128)	0
dropout_1 (Dropout)	(None, 22, 22, 128)	0
conv2d_6 (Conv2D)	(None, 20, 20, 256)	295168
batch_normalization_6 (Batch Normalization)	(None, 20, 20, 256)	1024
max_pooling2d_2 (MaxPooling2D)	(None, 10, 10, 256)	0
dropout_2 (Dropout)	(None, 10, 10, 256)	0
flatten (Flatten)	(None, 25600)	0
dense (Dense)	(None, 256)	6553856
batch_normalization_7 (Batch Normalization)	(None, 256)	1024
dense_1 (Dense)	(None, 128)	32896
batch_normalization_8 (Batch Normalization)	(None, 128)	512
dense_2 (Dense)	(None, 5)	645
Total params: 7,658,629		
Trainable params: 7,656,197		
Non-trainable params: 2,432		

Fig. 10: Script Photo Automation

Problem Encounter: Overfitting

- Complex Model: With its 7.6 million parameters, the complex model is learning very detailed features from the data.
- high level of detail can be a disadvantage if the training dataset is not large or diverse enough.
- The model starts learning noise and errors in the data as if they were significant features, leading to overfitting.
- It might perform well on the training data, it could perform poorly on new, unseen data because it has learned to fit the training data too closely.

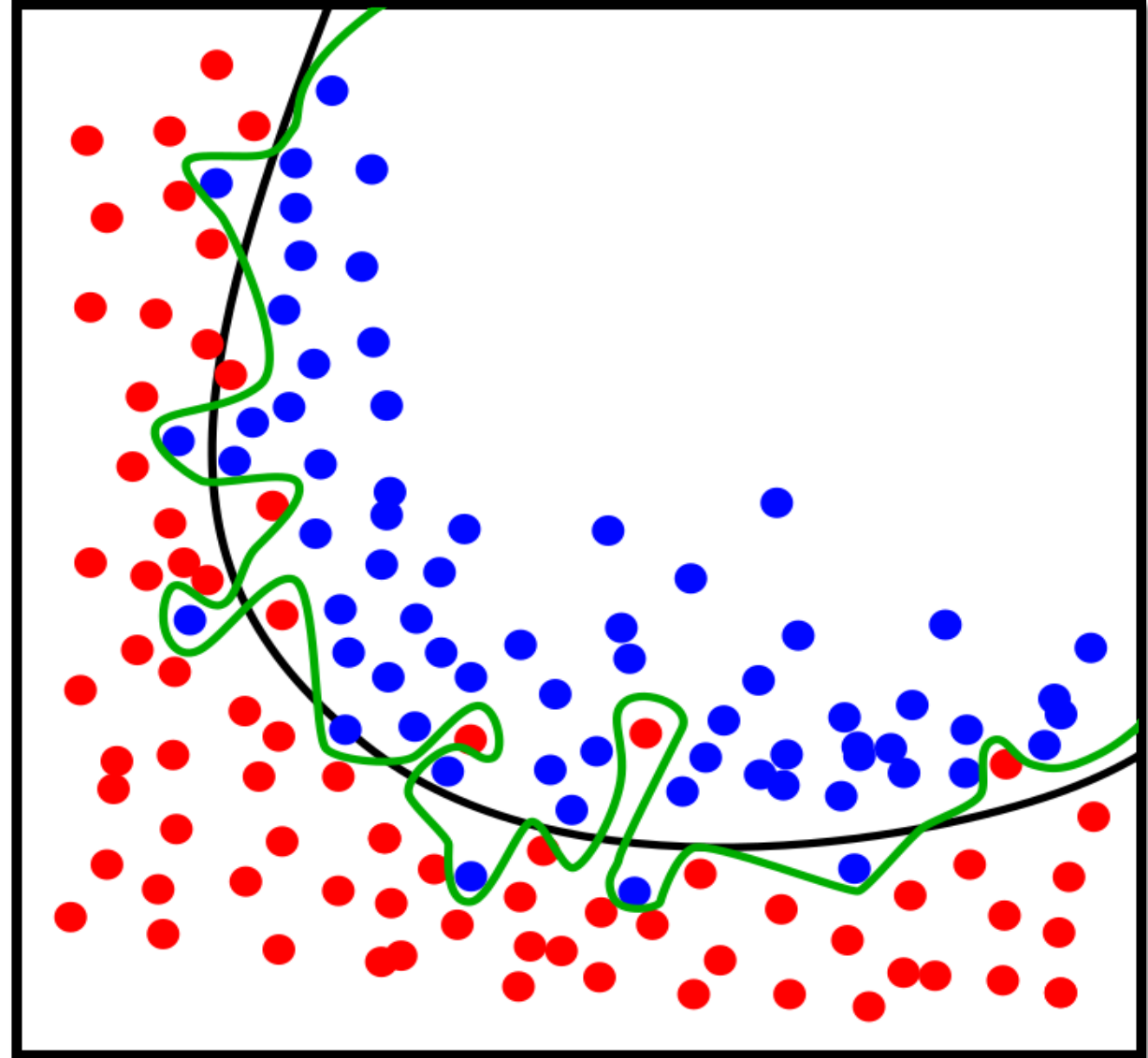


Fig. 11: Script Photo Automation

Model Architecture

Model: "simple_cnn_model"

Layer (type)	Output Shape	Param #
conv2d_27 (Conv2D)	(None, 98, 98, 64)	640
batch_normalization_35 (Batch Normalization)	(None, 98, 98, 64)	256
max_pooling2d_11 (MaxPooling2D)	(None, 49, 49, 64)	0
dropout_15 (Dropout)	(None, 49, 49, 64)	0
flatten_3 (Flatten)	(None, 153664)	0
dense_11 (Dense)	(None, 5)	768325
Total params: 769221 (2.93 MB)		
Trainable params: 769093 (2.93 MB)		
Non-trainable params: 128 (512.00 Byte)		

Fig. 12: Edited Model

- TensorFlow's Keras API, .
- Input Layer: The first layer is a 2D convolutional layer (Conv2D) with 64 filters, each with a kernel size of 3x3.
- Activation function: ReLU
- Batch Normalization: maintains the mean output close to 0 and the output standard deviation close to 1.
- Max Pooling: A 2D layer follows, with a pool size of 2x2.
- Dropout: This layer randomly sets a fraction (20% in this case) of the input units to zero at each update during training time. This helps prevent overfitting.
- Flatten: flattens the output of the previous layers into a single long feature vector
- Output Layer: 5 units and a softmax activation function. where each of the 5 units corresponds our class categorization problem

Training



Fig. 13: Classes Display



Fig. 14: Eigen Faces of the Dataset

Results

```
32/32 [=====] - 1s 16ms/step
```

	precision	recall	f1-score	support
1	1.00	1.00	1.00	265
2	1.00	1.00	1.00	258
3	1.00	1.00	1.00	256
4	1.00	1.00	1.00	241
accuracy			1.00	1020
macro avg	1.00	1.00	1.00	1020
weighted avg	1.00	1.00	1.00	1020

Fig. 4: Automation Levels

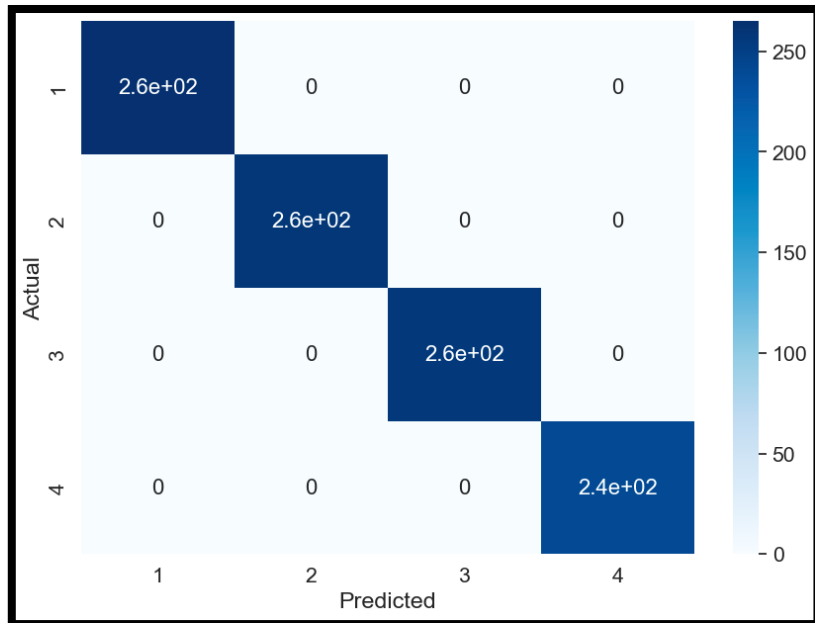


Fig. 11: Confusion Matix Accuracy

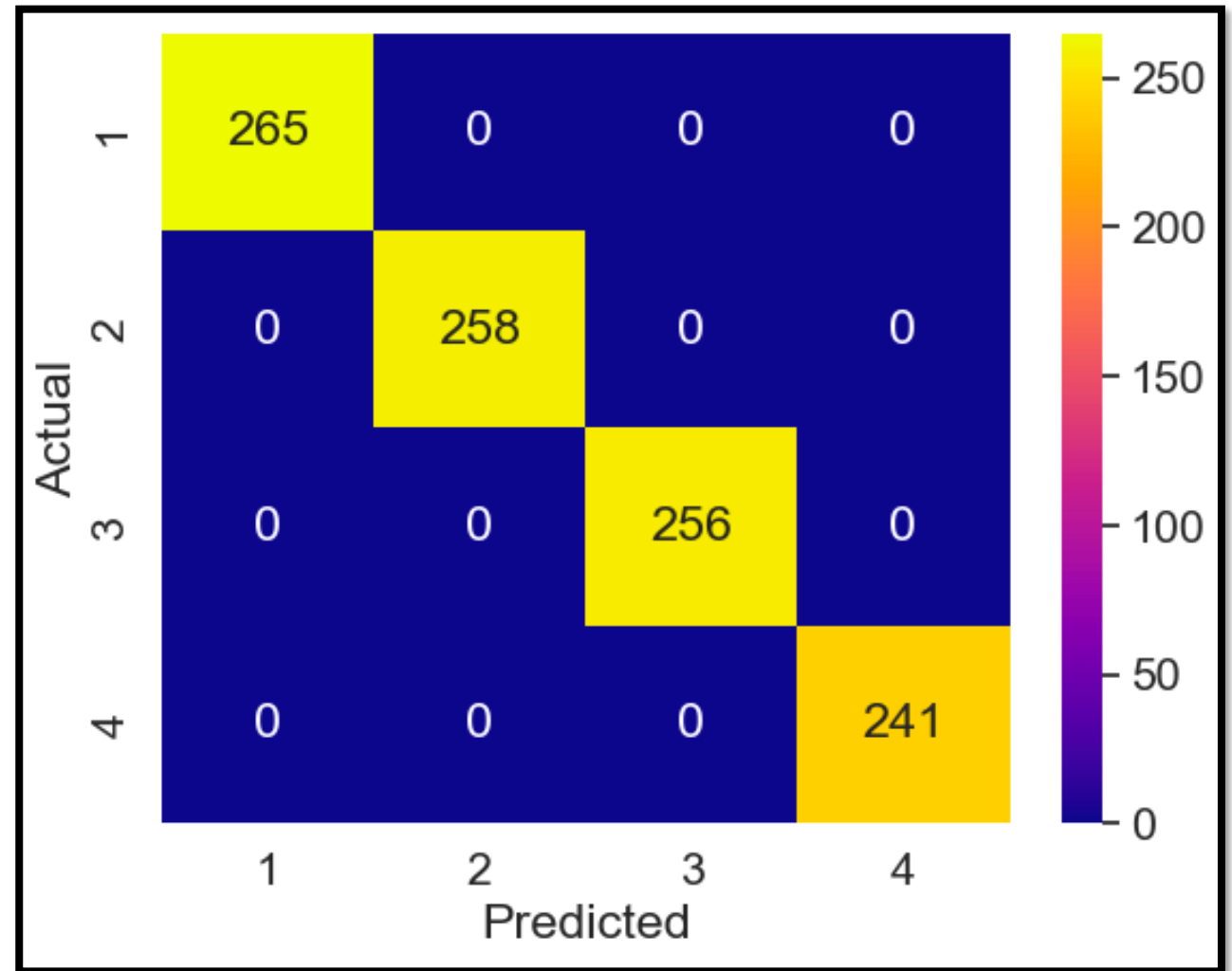


Fig. 3: Script Photo Automation

Results

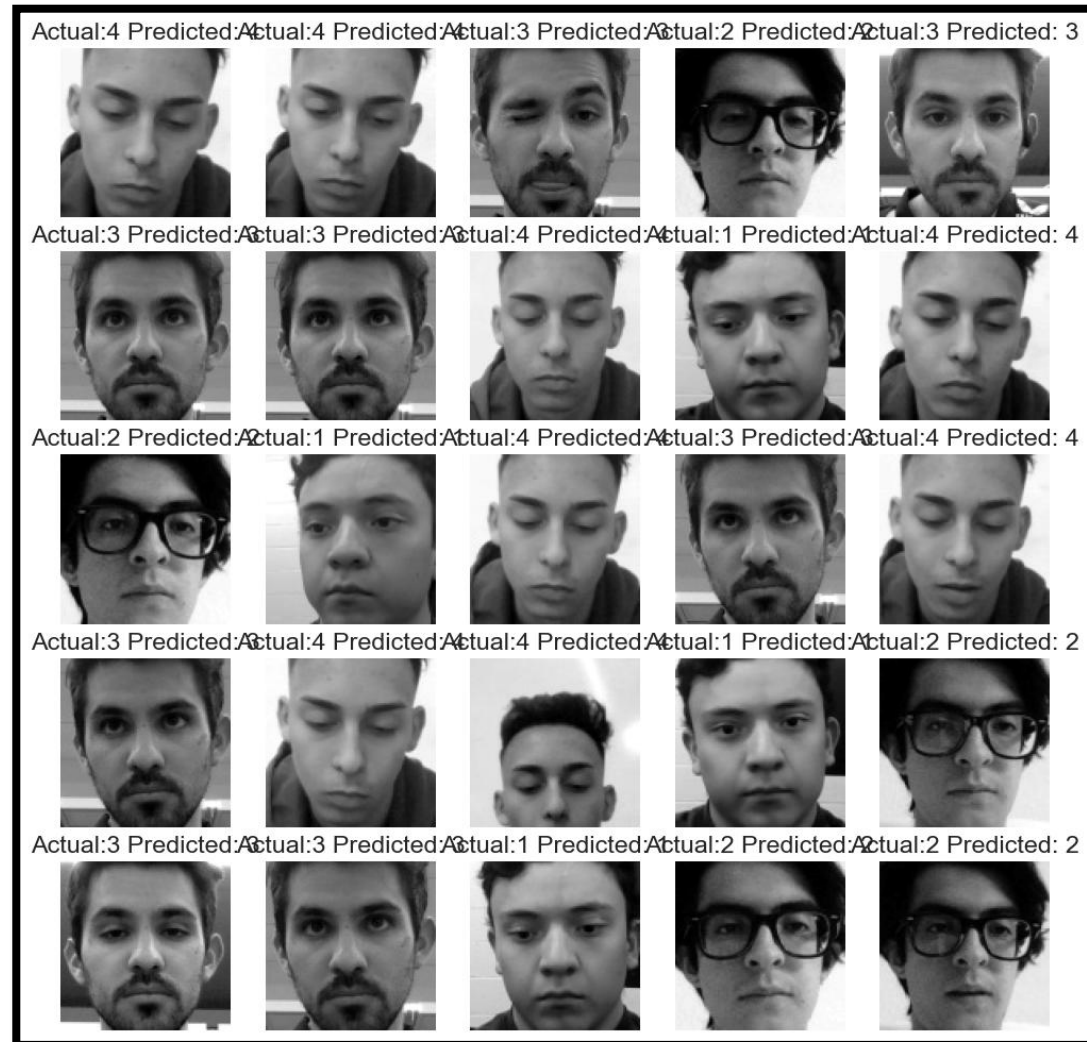


Fig. 12: Sampe Results

Gradient-weighted Class Activation Mapping

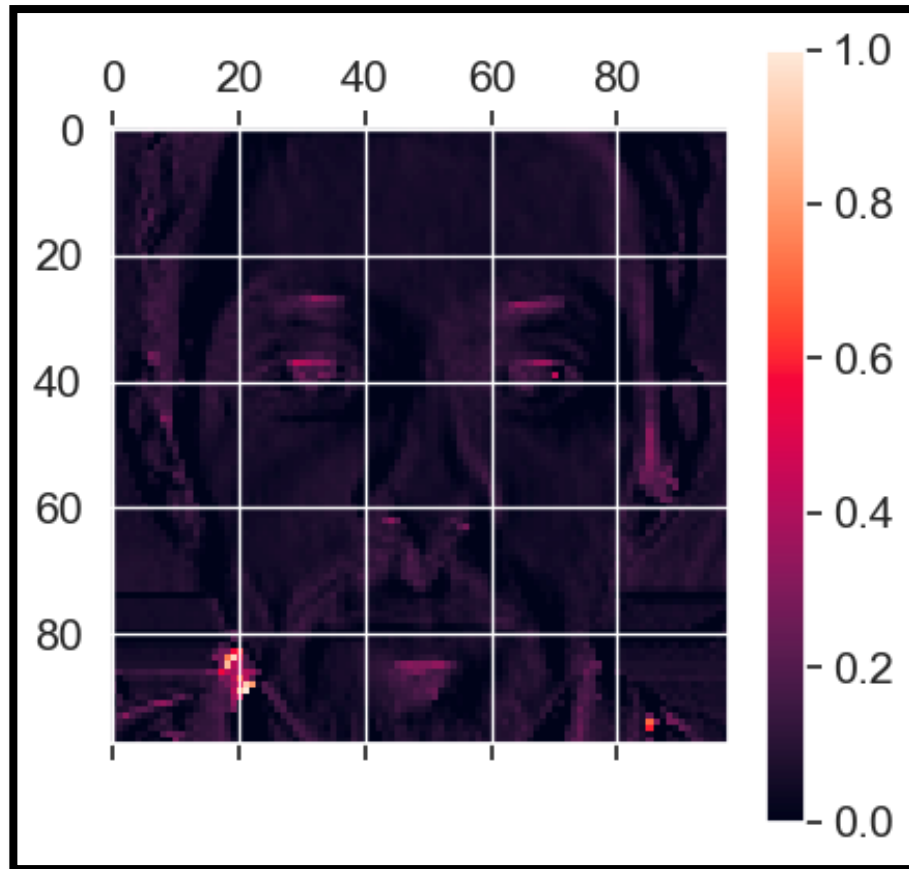


Fig. 14:Heatmap Weight



Fig. 15: Weight Calculation Classes

Gradient-weighted Class Activation Mapping

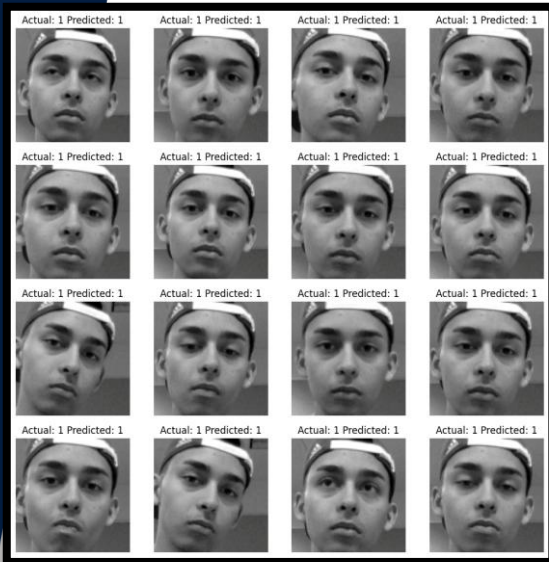


Fig. 16: Derek + Hat

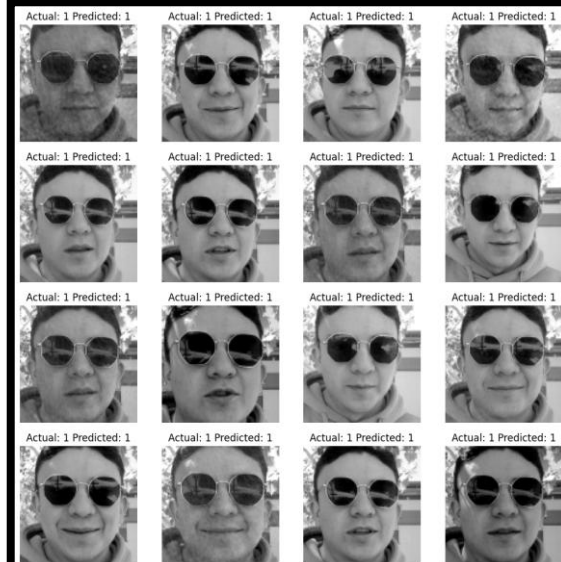


Fig. 17: Fernando + Glasses

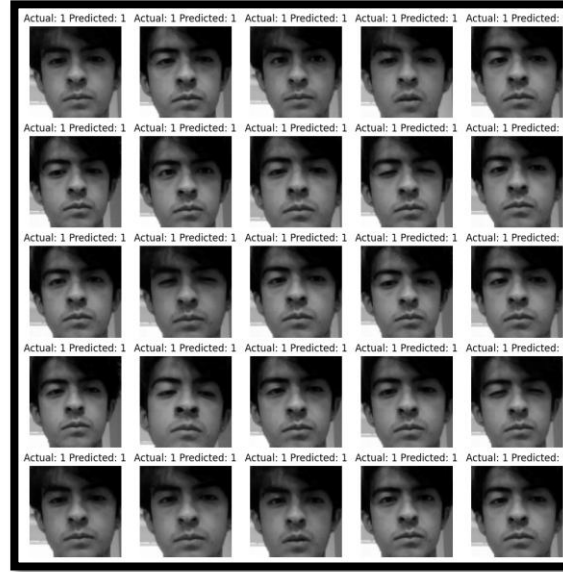


Fig. 18: Francisco – No Glasses

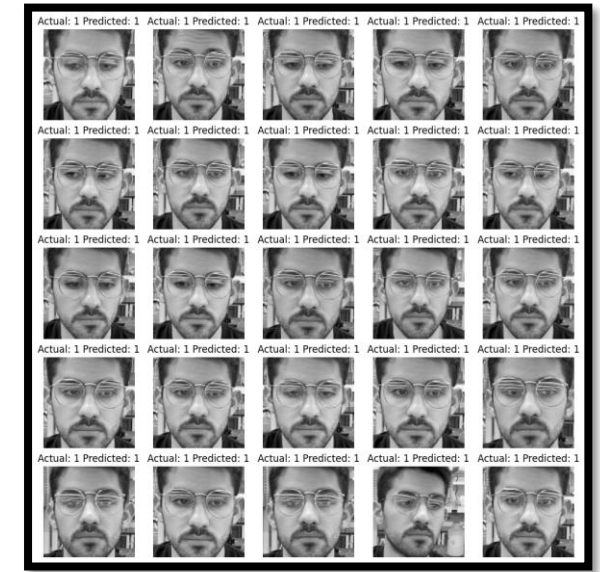


Fig. 19: Marco + Glasses

Summary

Our model has proven to be a reliable implementation of a CNN. However, one significant challenge we've encountered is overfitting, particularly when the dataset is small. This underscores the importance of data size in ensuring the model's robustness. Scaling up the project to a larger dataset would undoubtedly require higher computational power, considering factors such as processing time, data collection time, and analysis time.

This project has promising applications beyond its current scope. For instance, it could be expanded to serve as an identification feature for students during exams or for simple security process.

Takeaways: future & details

1. **Effective CNN Implementation:** Demonstrated CNN's effectiveness for the task.
2. **Overfitting Challenge:** Addressing overfitting with small datasets is crucial.
3. **Data Size's Significance:** Larger datasets improve model robustness, but require more computational resources.
4. **Working as a Team:** Efficient processing.
5. **Future Development:** Continue with a larger dataset.

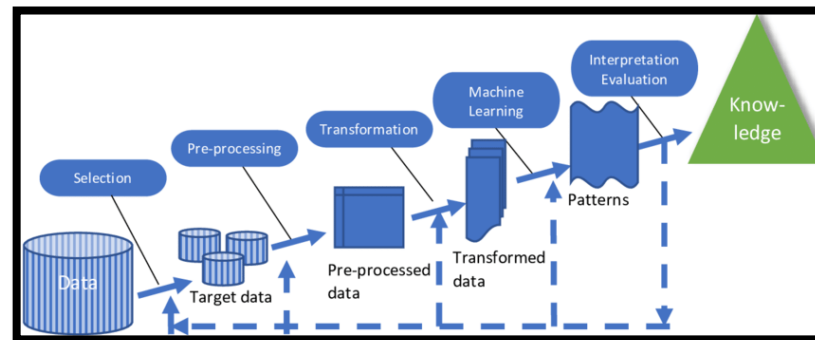


Fig. 16:ML Process

Thank you

Team 5:

- Fernando Sepulveda
- Derek Cisneros
- Marco Garcia Fernandez
- Francisco Parra

Questions?

