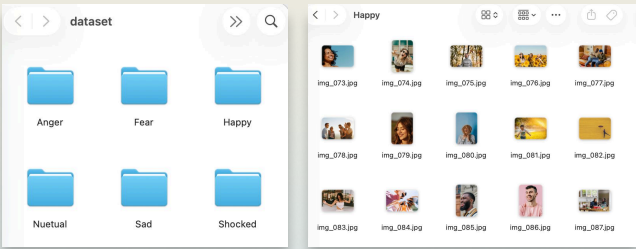


# Facial Dataset

## INTRODUCTION

The dataset contains **144 facial** images organized through a cross-structure of emotion. It employs dual labeling (visual and contextual) along with metadata annotation to make the logic of data construction explicit.



The dataset consists of 144 images, with 24 images collected for each of the six emotion categories.

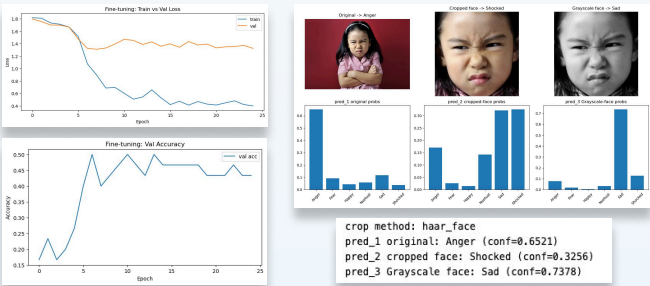
	A	B	C	D	E	F	G	H
1	image_id	emotion	context	eyes	mouth	eyebrow	intensity	social_state
2	img_001	sad	personal	downcast	open	furrowed	3	isolated
3	img_002	sad	personal	downcast	downturned	furrowed	2	isolated
4	img_003	sad	personal	closed	open	furrowed	3	isolated
5	img_004	sad	personal	downcast	downturned	furrowed	2	isolated
6	img_005	sad	personal	downcast	open	neutral	2	reactive
7	img_006	sad	personal	wide	neutral	neutral	2	reactive
8	img_007	sad	personal	downcast	downturned	neutral	2	isolated
9	img_008	sad	personal	downcast	neutral	neutral	1	reactive
10	img_009	sad	public	downcast	neutral	neutral	1	isolated
11	img_010	sad	personal	narrow	downturned	furrowed	2	isolated

Emotion labels were manually annotated for each image in an Excel metadata sheet.

## APPROACH 1

### Decontextualizing Emotion Computation

This approach uses a controlled comparison: it runs the ResNet18-based emotion model on original images and decontextualized images (cropped face, grayscale), then compares label, confidence, and accuracy changes to measure how context affects emotion recognition.



Mild overfitting occurs after early epochs

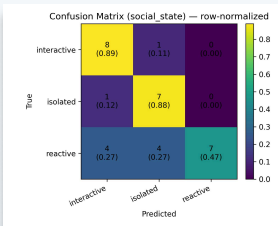
Predictions change under contextual removal

by Yirun Ye

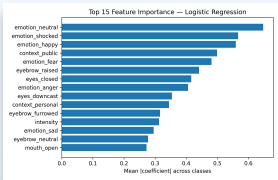
## APPROACH 2

### Computing Social State from Facial Structure

This approach explores whether social behaviour can be computationally inferred from facial geometry, emotion labels, and contextual metadata, reframing emotion recognition as a model of social interpretation.



Confusion Matrix



Feature Importance

#### Dataset + Model

127 valid samples  
3 classes: interactive / isolated / reactive  
Accuracy: 0.69

#### Findings

Interactive / isolated → stable prediction  
Reactive → high confusion  
Social state overlaps in facial cues  
Not purely visual → context matters

#### Key signals

emotion  
context  
eyebrow movement  
eye closure

Social behaviour emerges from combined cues, not a single feature.

by Shuran Zhang

## SHARED OBSERVATION

Both approaches reveal that facial interpretation is not purely visual.

**When context is removed (Approach 1)**, emotion predictions shift and confidence decreases.

**When context and metadata are structured (Approach 2)**, social\_state becomes partially predictable but remains ambiguous in transitional cases.

This suggests that facial meaning is not fixed within the image itself.

Rather, it emerges from the interaction between **facial cues, contextual information, and computational modelling**.

Machine learning here does not simply recognise emotion — it operationalises how social interpretation is constructed.

## ACKNOWLEDGEMENTS

### Dataset construction

**Yirun** collected and labelled the Anger, Fear, and Sad image sets.

**Shuran** collected and labelled the Happy, Neutral, and Shocked image sets, and added the Social\_State tags.

### Poster Production

**Yirun** is responsible for developing the overall poster framework, including the introduction and individual section.

**Shuran** is responsible for organizing the observation findings and contributing her individual section.