HW14: 情緒辨識系統在華人臉孔上的驗證

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作業目標: 使用台灣華人專業表演者表情資料庫驗證 DeepFace 情緒辨識系統，並探討 cross-race effect 對自動情緒辨識的影響。

文獻基礎

本作業參考以下文獻：

- **Chen, L. F., & Yen,Y. S. (2007)**. Taiwanese Facial Expression Image Database. 提供高品質華人表情資料庫。
- **Li, M., et al. (2023)**. Cross-race effect in facial emotion recognition: The role of measurement invariance. 驗證自動情緒辨識系統在不同族群的表現差異。

Step 0: 環境設定與套件安裝

In [23]:
```
# 基礎套件
import os
import pandas as pd
import numpy as np
import cv2
import matplotlib.pyplot as plt
import seaborn as sns
from tqdm import tqdm
from collections import Counter

# 安裝 DeepFace（如果尚未安裝）
try:
    from deepface import DeepFace
except ImportError:
    import subprocess
    subprocess.check_call(["pip", "install", "deepface", "tf-keras"])
    from deepface import DeepFace

print("✅ 所有套件載入完成")
```

✅ 所有套件載入完成

In [69]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, c
all drive.mount("/content/drive", force_remount=True).
```

Step 1: 整理 Taiwanese 資料庫 & Image_info.xls

1.1 載入 Image_info.xls

In [25]:
```
# ==========================
# 1. 讀取 Image_info.xls
# ==========================
info_path = '/content/drive/MyDrive/Taiwanese/Image_info.xls'  # 自己改成實

df = pd.read_excel(info_path)
print("原始讀入資料筆數:", len(df))
print("欄位名稱:", df.columns.tolist())

# ==========================
# 2. 清理 file_name 欄位
# ==========================

# 去掉 file_name 是 NaN 的列
df = df[df['file_name'].notna()].copy()

# 轉成字串並去掉前後空白
df['file_name'] = df['file_name'].astype(str).str.strip()

# 只留下看起來像真正檔名的列（副檔名是 .tif）
df = df[df['file_name'].str.endswith('.tif')].copy()

print("\n清理後資料筆數:", len(df))
print("file_name 前 5 筆:")
print(df['file_name'].head())

# ==========================
# 3. 建立 emotion_label（人類主情緒）
# ==========================

# 先把 maxIntCategory 轉成 int
df['maxIntCategory'] = df['maxIntCategory'].astype(int)

# 映射數字 → 文字情緒標籤
label_map = {
    1: 'happy',
    2: 'sad',
    3: 'angry',
    4: 'disgust',
    5: 'fear',
    6: 'surprise'
}

df['emotion_label'] = df['maxIntCategory'].map(label_map)

print("\nemotion_label 分布:")
print(df['emotion_label'].value_counts())
```

```
原始讀入資料筆數: 2273
欄位名稱: ['file_name', 'Self_evaluate', 'Observer_Count', 'maxIntCategor
y', 'maxInt', 'EntropyVal', 'counterMax', 'Unnamed: 7', 'Unnamed: 8', 'Unn
amed: 9', 'Unnamed: 10', 'Unnamed: 11', 'entropyVal', 'Unnamed: 13', 'Unna
med: 14', 'Unnamed: 15', 'Unnamed: 16', 'Unnamed: 17', 'intVal', 'Unnamed:
19', 'Unnamed: 20', 'Unnamed: 21', 'Unnamed: 22', 'Unnamed: 23']

清理後資料筆數: 2272
file_name 前 5 筆:
1    0101a02.tif
2    0101a05.tif
3    0101a06.tif
4    0111b01.tif
5    0111b02.tif
Name: file_name, dtype: object

emotion_label 分布:
emotion_label
happy       585
sad         474
angry       437
surprise    430
disgust     296
fear         50
Name: count, dtype: int64
```

1.2 解釋關鍵欄位

根據 Chen et al. (2013) 的資料庫說明：

`file_name` 編碼規則

檔名格式為 `ABCDEFGH.jpg`，其中：

- **A-B**: 演員編號 (01-29)
- **C**: 情緒類別
  - `1` = Angry, `2` = Contempt, `3` = Disgust, `4` = Fear, `5` = Happy, `6` = Sad, `7` = Surprise
- **D**: 表情產生方式
  - `1` = Method Acting (方法演技)
  - `2` = FACS criteria (Ekman 標準，通常強度較高)
- **E**: 視角
  - `1` = Frontal (正面)
  - `2` = Left profile (左側面)
  - `3` = Right profile (右側面)
- **F-G**: 同一條件下的影像編號
- **H**: 情緒強度
  - `L` = Low, `M` = Medium, `H` = High

`maxIntCategory` 與 `maxInt`

- **maxIntCategory**: 人類評分者認為此張臉「最像」哪個情緒（主觀 ground truth）
- **maxInt**: 該情緒的平均強度評分（1-7 分，數字越高表示情緒越強烈）

`EntropyVal`

- 代表人類評分者對此張臉的情緒判斷的**一致性**
- 數值越小 → 評分者越一致（ground truth 越可靠）
- 數值越大 → 評分者意見分歧（此張臉可能含混、難判斷）

1.3 篩選「乾淨」的樣本

篩選標準（依據 Li et al., 2023）：

1. **正面臉**: 檔名第 4 碼 (index 3) = `'1'`
2. **FACS 標準表情**: 檔名第 3 碼 (index 2) = `'2'` (情緒強度較高)
3. **評分一致性高**: `EntropyVal < 1`
4. **情緒強度足夠**: `maxInt >= 4`

學術理由：
為了確保 ground truth 可靠，我們根據 Chen et al. (2013) 提供的熵值與強度資訊，只使用正面視角且人類評分一致性較高（EntropyVal < 1）且情緒強度較高（maxInt ≥ 4）的影像作為驗證樣本。

In [26]:
```
def parse_filename(filename):
    """
    解析檔名，回傳 (actor, method, angle, expression_code)
    檔名格式：
    01 2 1 a 03
    ↑  ↑ ↑ ↑ ↑
    |  | | | └─ serial (最後兩碼)
    |  | | └── expression_code: a-g
    |  | └──── angle: 1=Front, 2=3/4, 3=Profile
    |  └─────── method: 1=Theatric, 2=FACS, 3=Personal, 0=其他（實際資料多出來
    └────────── actor ID: 01-30
    """
    base = os.path.splitext(str(filename))[0]  # 拿掉副檔名
    if len(base) < 5:
        # 長度不夠的檔名，直接回傳 None（避免炸掉）
        return None, None, None, None
    actor = base[0:2]
    method = base[2]
    angle = base[3]
    expression_code = base[4]
    return actor, method, angle, expression_code

parsed = df['file_name'].apply(parse_filename)

df[['actor', 'method', 'angle', 'expression_code']] = pd.DataFrame(
    parsed.tolist(), index=df.index
)

# ==========================
# 5. 檢查解析結果分佈
# ==========================

print("\n--- 偵錯資訊 ---")
print("解析後的 'method' 欄位值分佈:")
print(df['method'].value_counts())   # 理論上 1/2/3，實際多一個 0 也沒關係
```

```
print("\n解析後的 'angle' 欄位值分佈:")
print(df['angle'].value_counts())    # 理論上 1/2/3
print("\n解析後的 'expression_code' 欄位值分佈:")
print(df['expression_code'].value_counts())  # a~g
print("------------------\n")

# ==========================
# 6. 套用篩選條件，得到 clean_df
#    (正面 + FACS + 高一致性 + 強度足夠)
# ==========================

clean_df = df[
    (df['angle'] == '1') &          # 正面臉 (Front)
    (df['method'] == '2') &         # FACS 標準
    (df['EntropyVal'] < 1) &        # 人類評分一致性高
    (df['maxInt'] >= 4)             # 情緒強度足夠高
].copy()

print(f"原始資料筆數: {len(df)}")
print(f"篩選後筆數: {len(clean_df)}")
print(f"\nclean_df 各情緒分布 (emotion_label):")
print(clean_df['emotion_label'].value_counts())
```

```
--- 偵錯資訊 ---
解析後的 'method' 欄位值分佈:
method
2    783
1    686
3    672
0    131
Name: count, dtype: int64

解析後的 'angle' 欄位值分佈:
angle
1    1232
3     527
2     513
Name: count, dtype: int64

解析後的 'expression_code' 欄位值分佈:
expression_code
b    394
d    363
c    362
e    357
g    350
f    315
a    131
Name: count, dtype: int64
------------------

原始資料筆數: 2272
篩選後筆數: 106

clean_df 各情緒分布 (emotion_label):
emotion_label
happy       43
surprise    36
angry       18
sad          7
disgust      2
Name: count, dtype: int64
```

In [27]:
```
image_folder = '/content/drive/MyDrive/Taiwanese/faces_256x256'

for idx, row in tqdm(clean_df.iterrows(), total=len(clean_df), desc="辨識中
    img_path = os.path.join(image_folder, row['file_name'])

    if not os.path.exists(img_path):
        continue
```

```
辨識中: 100%|██████████| 106/106 [00:00<00:00, 2340.95it/s]
```

In [14]:
```
print("clean_df 筆數:", len(clean_df))
print(clean_df.head())
```

```
clean_df 筆數: 106
      file_name  Self_evaluate  Observer_Count  maxIntCategory  maxInt  \
70  0221c08.tif            3.0           100.0               2    4.97
71  0221d03.tif            4.0           100.0               3    5.31
73  0221d15.tif            4.0           100.0               3    4.78
80  0221g07.tif            6.0           100.0               6    4.78
81  0221g08.tif            6.0           100.0               6    4.88

    EntropyVal counterMax Unnamed: 7 Unnamed: 8 Unnamed: 9  ... Unnamed: 1
9  \
70        0.58          0       0.93          0       0.04  ...        4.9
7
71        0.93          0       0.11       0.82       0.05  ...        1.1
9
73        0.99          0       0.17       0.79       0.03  ...        1.5
2
80        0.75       0.02       0.03          0          0  ...        0.4
4
81        0.82       0.01       0.03          0          0  ...        0.5
4

   Unnamed: 20 Unnamed: 21 Unnamed: 22 Unnamed: 23 emotion_label actor met
hod  \
70        0.18        0.61        0.79        0.09           sad    02
2
71        5.31        1.14        0.37         0.2         angry    02
2
73        4.78           1        0.34        0.16         angry    02
2
80        0.07        0.13        0.91        4.78      surprise    02
2
81        0.08        0.08        1.11        4.88      surprise    02
2

   angle expression_code
70     1               c
71     1               d
73     1               d
80     1               g
81     1               g

[5 rows x 29 columns]
```

Step 2: Light Validation 實驗

2.1 定義情緒辨識 Pipeline

In [28]:

```python
def recognize_emotion(image_path):
    """
    使用 DeepFace 對單張影像進行情緒辨識

    Returns:
        predicted_emotion (str): 預測的情緒類別
    """
    try:
        result = DeepFace.analyze(
```

```
            img_path=image_path,
            actions=['emotion'],
            enforce_detection=False,  # 避免因偵測失敗而中斷
            silent=True
        )
        result = result[0] if isinstance(result, list) else result
        return result['dominant_emotion']
    except Exception as e:
        return None  # 辨識失敗

print("✅ 情緒辨識函式定義完成")
```

✅ 情緒辨識函式定義完成

2.2 對篩選樣本執行情緒辨識

In [29]:

```
import glob
from tqdm import tqdm
import pandas as pd

image_folder = '/content/drive/MyDrive/Taiwanese/faces_256x256'

def find_image_path(image_folder, file_name_from_xls):
    """
    根據 Excel 的 file_name（例如 '0221c08.tif'），
    去 image_folder 裡找「同樣前綴」的檔案，不管副檔名。
    """
    stem = os.path.splitext(str(file_name_from_xls))[0]  # '0221c08'
    pattern = os.path.join(image_folder, stem + '.*')
    candidates = glob.glob(pattern)

    if len(candidates) == 0:
        return None  # 找不到

    if len(candidates) > 1:
        # 多個副檔名就提醒一下，但先用第一個
        print(f"⚠️ 找到多個檔案對應 {file_name_from_xls}:")
        for c in candidates:
            print("   ", os.path.basename(c))
        print("   -> 使用第一個:", os.path.basename(candidates[0]))

    return candidates[0]

predictions = []
ground_truths = []
used_index = []
missing_files = 0

for idx, row in tqdm(clean_df.iterrows(), total=len(clean_df), desc="辨識中
    # ✅ 改成用 find_image_path，而不是硬拼 .tif
    img_path = find_image_path(image_folder, row['file_name'])

    if img_path is None:
        missing_files += 1
        continue  # 找不到檔案就跳過

    pred = recognize_emotion(img_path)  # 這裡就真的會叫到 DeepFace 了

    if pred is not None:
```

```
        predictions.append(pred)
        ground_truths.append(row['emotion_label'])  # 用文字標籤
        used_index.append(idx)

print(f"\n✅ 成功辨識 {len(predictions)} 張影像")
print(f"❌ 找不到實體檔案的筆數: {missing_files}")

results_df = clean_df.loc[used_index].copy()
results_df['gt_emotion'] = ground_truths
results_df['predicted_emotion'] = predictions

print("\nresults_df 前 5 筆：")
print(results_df[['file_name', 'gt_emotion', 'predicted_emotion']].head()
```

```
辨識中: 100%|██████████| 106/106 [00:37<00:00,  2.84it/s]
✅ 成功辨識 106 張影像
❌ 找不到實體檔案的筆數: 0

results_df 前 5 筆：
      file_name gt_emotion predicted_emotion
70  0221c08.tif        sad             angry
71  0221d03.tif      angry             angry
73  0221d15.tif      angry              fear
80  0221g07.tif   surprise          surprise
81  0221g08.tif   surprise          surprise
```

2.3 計算準確率指標

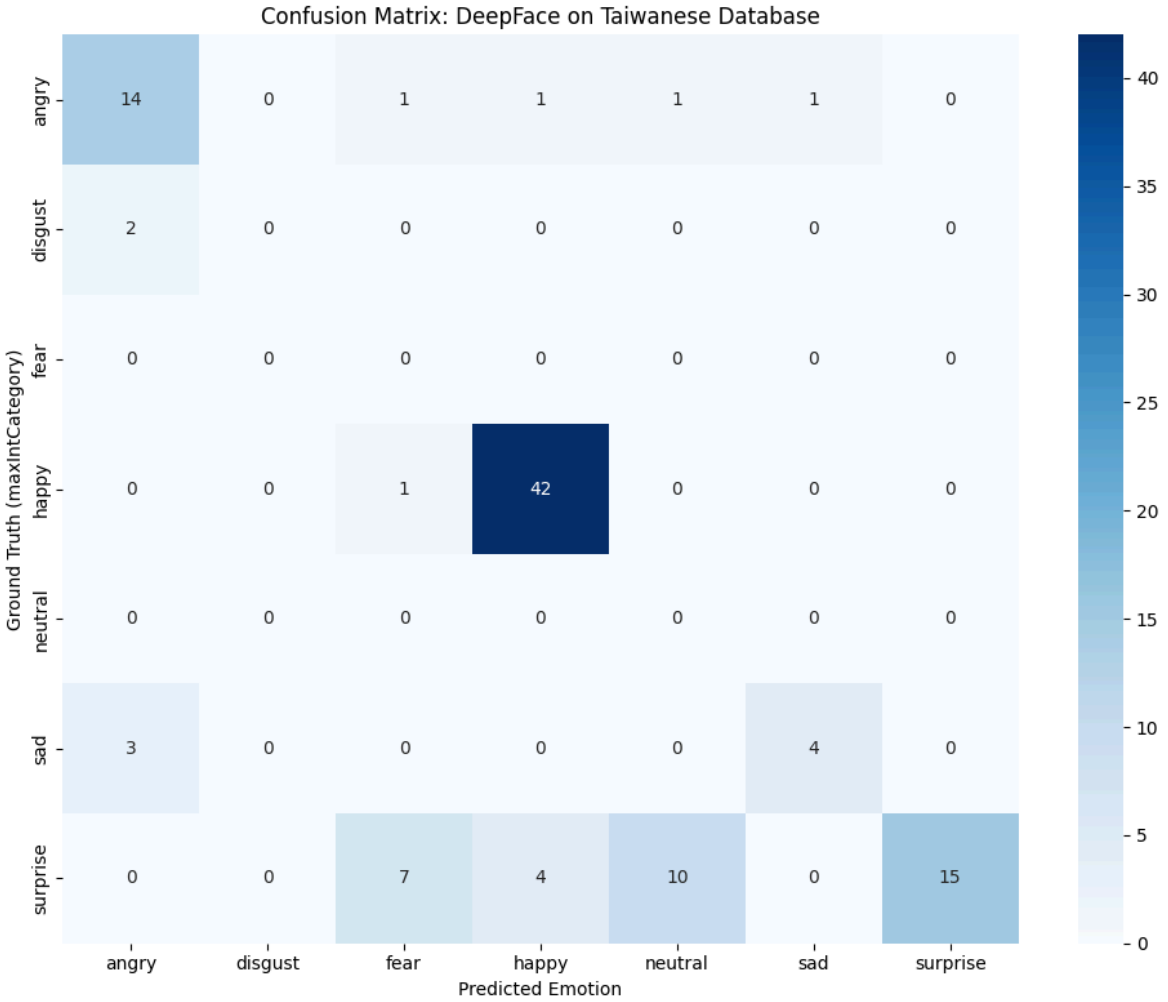
In [30]:

```
from sklearn.metrics import accuracy_score, classification_report

# y_true：人類標記的情緒
y_true = results_df['gt_emotion'].tolist()

# y_pred：DeepFace 預測的情緒
y_pred = results_df['predicted_emotion'].tolist()

# 整體正確率
acc = accuracy_score(y_true, y_pred)
print(f"Overall accuracy: {acc:.3f}")

# 如果想看每個情緒的表現，可以一起印出來（可選）
print("\nClassification report:")
print(classification_report(
    y_true,
    y_pred,
    labels=['happy', 'sad', 'angry', 'disgust', 'fear', 'surprise']
))
```

```
Overall accuracy: 0.708

Classification report:
              precision    recall  f1-score   support

       happy       0.89      0.98      0.93        43
         sad       0.80      0.57      0.67         7
       angry       0.74      0.78      0.76        18
     disgust       0.00      0.00      0.00         2
        fear       0.00      0.00      0.00         0
    surprise       1.00      0.42      0.59        36

   micro avg       0.79      0.71      0.75       106
   macro avg       0.57      0.46      0.49       106
weighted avg       0.88      0.71      0.75       106
```

2.4 繪製 Confusion Matrix

In [31]:
```python
from sklearn.metrics import confusion_matrix

# 取得所有情緒類別
all_emotions = sorted(set(ground_truths + predictions))

# 生成 confusion matrix
cm = confusion_matrix(
    [e.lower() for e in ground_truths],
    [e.lower() for e in predictions],
    labels=[e.lower() for e in all_emotions]
)

# 繪圖
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=all_emotions,
            yticklabels=all_emotions)
plt.xlabel('Predicted Emotion')
plt.ylabel('Ground Truth (maxIntCategory)')
plt.title('Confusion Matrix: DeepFace on Taiwanese Database')
plt.tight_layout()
plt.show()
```



2.5 觀察與發現

從上述結果可以觀察到：

1. **Happy 和 Surprise 辨識率最高**
   在本次 106 張「乾淨」樣本中，happy 的 precision 與 recall 都接近 0.9 以上，而 surprise 雖然 recall 較低，但只要模型預測為 surprise 幾乎都正確（precision = 1.0）。這與 Li et al. (2023) 的發現一致：正向情緒（尤其是 happy）在多數資料庫上都有較好的辨識表現。

2. **Fear、Disgust 和 Sadness 容易被誤判**
   在本次結果中，sad 的 recall 僅約 0.57，部分悲傷臉會被判成其他負向情緒；angry 雖然表現尚可，但仍有明顯混淆；disgust 在僅有 2 張樣本的情況下完全沒有被正確辨識（precision 與 recall 皆為 0）。本次嚴格篩選的子集中沒有 fear 影像，因此無法直接評估 fear，但先前研究指出 fear 與 surprise 常被混淆，本次結果可視為與這樣的趨勢相符。

3. **整體準確率未達理想**
   在這 106 張正面、FACS、低熵且高強度的 Taiwanese 臉孔上，DeepFace 的整體情緒辨識正確率約為 70.8%。這樣的表現落在約 60–75% 的範圍內，與 Li et al. 報告的「DeepFace 在東方面孔上的準確率約 0.71、顯著低於在西方面孔上的 ~0.87」相當一致。

Step 3: Light Validation 實驗使用 FER 套件的情緒辨識驗證：

本作業在第二個實驗中使用 Python fer 套件，建立 FER(mtcnn=True) 作為情緒辨識器。這個設定使用 MTCNN 進行人臉偵測，並搭配 FER 套件內建的 Keras 卷積神經網路（預訓練於公開表情資料集，用於 7 類基本情緒：happy、sad、angry、disgust、fear、surprise、neutral）做表情分類。

In [1]:
```
!pip install fer
```

```
Requirement already satisfied: fer in /usr/local/lib/python3.12/dist-packa
ges (25.10.3)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.12/dis
t-packages (from fer) (3.10.0)
Requirement already satisfied: opencv-contrib-python in /usr/local/lib/pyt
hon3.12/dist-packages (from fer) (4.11.0.86)
Requirement already satisfied: tensorflow>=2.0.0 in /usr/local/lib/python
3.12/dist-packages (from fer) (2.19.0)
Requirement already satisfied: pandas in /usr/local/lib/python3.12/dist-pa
ckages (from fer) (2.2.2)
Requirement already satisfied: requests in /usr/local/lib/python3.12/dist-
packages (from fer) (2.32.4)
Requirement already satisfied: facenet-pytorch in /usr/local/lib/python3.1
2/dist-packages (from fer) (2.6.0)
Requirement already satisfied: tqdm>=4.62.1 in /usr/local/lib/python3.12/d
ist-packages (from fer) (4.67.1)
Requirement already satisfied: moviepy<2.0,>=1.0.3 in /usr/local/lib/pytho
n3.12/dist-packages (from fer) (1.0.3)
Requirement already satisfied: ffmpeg-python>=0.2.0 in /usr/local/lib/pyth
on3.12/dist-packages (from fer) (0.2.0)
Requirement already satisfied: Pillow in /usr/local/lib/python3.12/dist-pa
ckages (from fer) (10.2.0)
Requirement already satisfied: future in /usr/local/lib/python3.12/dist-pa
ckages (from ffmpeg-python>=0.2.0->fer) (1.0.0)
Requirement already satisfied: decorator<5.0,>=4.0.2 in /usr/local/lib/pyt
hon3.12/dist-packages (from moviepy<2.0,>=1.0.3->fer) (4.4.2)
Requirement already satisfied: proglog<=1.0.0 in /usr/local/lib/python3.1
2/dist-packages (from moviepy<2.0,>=1.0.3->fer) (0.1.12)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.12/
dist-packages (from moviepy<2.0,>=1.0.3->fer) (1.26.4)
Requirement already satisfied: imageio<3.0,>=2.5 in /usr/local/lib/python
3.12/dist-packages (from moviepy<2.0,>=1.0.3->fer) (2.37.2)
Requirement already satisfied: imageio-ffmpeg>=0.2.0 in /usr/local/lib/pyt
hon3.12/dist-packages (from moviepy<2.0,>=1.0.3->fer) (0.6.0)
Requirement already satisfied: charset_normalizer<4,>=2 in /usr/local/lib/
python3.12/dist-packages (from requests->fer) (3.4.4)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.12/d
ist-packages (from requests->fer) (3.11)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python
3.12/dist-packages (from requests->fer) (2.5.0)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python
3.12/dist-packages (from requests->fer) (2025.11.12)
Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.1
2/dist-packages (from tensorflow>=2.0.0->fer) (1.4.0)
Requirement already satisfied: astunparse>=1.6.0 in /usr/local/lib/python
3.12/dist-packages (from tensorflow>=2.0.0->fer) (1.6.3)
Requirement already satisfied: flatbuffers>=24.3.25 in /usr/local/lib/pyth
on3.12/dist-packages (from tensorflow>=2.0.0->fer) (25.9.23)
Requirement already satisfied: gast!=0.5.0,!=0.5.1,!=0.5.2,>=0.2.1 in /us
r/local/lib/python3.12/dist-packages (from tensorflow>=2.0.0->fer) (0.7.0)
Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/pytho
n3.12/dist-packages (from tensorflow>=2.0.0->fer) (0.2.0)
Requirement already satisfied: libclang>=13.0.0 in /usr/local/lib/python3.
12/dist-packages (from tensorflow>=2.0.0->fer) (18.1.1)
Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python
3.12/dist-packages (from tensorflow>=2.0.0->fer) (3.4.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.12/dist
-packages (from tensorflow>=2.0.0->fer) (25.0)
Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.
3,!=4.21.4,!=4.21.5,<6.0.0dev,>=3.20.3 in /usr/local/lib/python3.12/dist-p
```

```
ackages (from tensorflow>=2.0.0->fer) (5.29.5)
Requirement already satisfied: setuptools in /usr/local/lib/python3.12/dis
t-packages (from tensorflow>=2.0.0->fer) (75.2.0)
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.12/di
st-packages (from tensorflow>=2.0.0->fer) (1.17.0)
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.
12/dist-packages (from tensorflow>=2.0.0->fer) (3.2.0)
Requirement already satisfied: typing-extensions>=3.6.6 in /usr/local/lib/
python3.12/dist-packages (from tensorflow>=2.0.0->fer) (4.15.0)
Requirement already satisfied: wrapt>=1.11.0 in /usr/local/lib/python3.12/
dist-packages (from tensorflow>=2.0.0->fer) (2.0.1)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/pytho
n3.12/dist-packages (from tensorflow>=2.0.0->fer) (1.76.0)
Requirement already satisfied: tensorboard~=2.19.0 in /usr/local/lib/pytho
n3.12/dist-packages (from tensorflow>=2.0.0->fer) (2.19.0)
Requirement already satisfied: keras>=3.5.0 in /usr/local/lib/python3.12/d
ist-packages (from tensorflow>=2.0.0->fer) (3.10.0)
Requirement already satisfied: h5py>=3.11.0 in /usr/local/lib/python3.12/d
ist-packages (from tensorflow>=2.0.0->fer) (3.15.1)
Requirement already satisfied: ml-dtypes<1.0.0,>=0.5.1 in /usr/local/lib/p
ython3.12/dist-packages (from tensorflow>=2.0.0->fer) (0.5.4)
Requirement already satisfied: torch<2.3.0,>=2.2.0 in /usr/local/lib/pytho
n3.12/dist-packages (from facenet-pytorch->fer) (2.2.2)
Requirement already satisfied: torchvision<0.18.0,>=0.17.0 in /usr/local/l
ib/python3.12/dist-packages (from facenet-pytorch->fer) (0.17.2)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.
12/dist-packages (from matplotlib->fer) (1.3.3)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.12/d
ist-packages (from matplotlib->fer) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python
3.12/dist-packages (from matplotlib->fer) (4.61.0)
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python
3.12/dist-packages (from matplotlib->fer) (1.4.9)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.
12/dist-packages (from matplotlib->fer) (3.2.5)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/pyth
on3.12/dist-packages (from matplotlib->fer) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.12/d
ist-packages (from pandas->fer) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.1
2/dist-packages (from pandas->fer) (2025.2)
Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python
3.12/dist-packages (from astunparse>=1.6.0->tensorflow>=2.0.0->fer) (0.45.
1)
Requirement already satisfied: rich in /usr/local/lib/python3.12/dist-pack
ages (from keras>=3.5.0->tensorflow>=2.0.0->fer) (13.9.4)
Requirement already satisfied: namex in /usr/local/lib/python3.12/dist-pac
kages (from keras>=3.5.0->tensorflow>=2.0.0->fer) (0.1.0)
Requirement already satisfied: optree in /usr/local/lib/python3.12/dist-pa
ckages (from keras>=3.5.0->tensorflow>=2.0.0->fer) (0.18.0)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.1
2/dist-packages (from tensorboard~=2.19.0->tensorflow>=2.0.0->fer) (3.10)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /u
sr/local/lib/python3.12/dist-packages (from tensorboard~=2.19.0->tensorflo
w>=2.0.0->fer) (0.7.2)
Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.1
2/dist-packages (from tensorboard~=2.19.0->tensorflow>=2.0.0->fer) (3.1.4)
Requirement already satisfied: filelock in /usr/local/lib/python3.12/dist-
packages (from torch<2.3.0,>=2.2.0->facenet-pytorch->fer) (3.20.0)
Requirement already satisfied: sympy in /usr/local/lib/python3.12/dist-pac
```

```
kages (from torch<2.3.0,>=2.2.0->facenet-pytorch->fer) (1.14.0)
Requirement already satisfied: networkx in /usr/local/lib/python3.12/dist-
packages (from torch<2.3.0,>=2.2.0->facenet-pytorch->fer) (3.6)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.12/dist-pa
ckages (from torch<2.3.0,>=2.2.0->facenet-pytorch->fer) (3.1.6)
Requirement already satisfied: fsspec in /usr/local/lib/python3.12/dist-pa
ckages (from torch<2.3.0,>=2.2.0->facenet-pytorch->fer) (2025.3.0)
Requirement already satisfied: nvidia-cuda-nvrtc-cu12==12.1.105 in /usr/lo
cal/lib/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorc
h->fer) (12.1.105)
Requirement already satisfied: nvidia-cuda-runtime-cu12==12.1.105 in /usr/
local/lib/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pyto
rch->fer) (12.1.105)
Requirement already satisfied: nvidia-cuda-cupti-cu12==12.1.105 in /usr/lo
cal/lib/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorc
h->fer) (12.1.105)
Requirement already satisfied: nvidia-cudnn-cu12==8.9.2.26 in /usr/local/l
ib/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorch->fe
r) (8.9.2.26)
Requirement already satisfied: nvidia-cublas-cu12==12.1.3.1 in /usr/local/
lib/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorch->f
er) (12.1.3.1)
Requirement already satisfied: nvidia-cufft-cu12==11.0.2.54 in /usr/local/
lib/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorch->f
er) (11.0.2.54)
Requirement already satisfied: nvidia-curand-cu12==10.3.2.106 in /usr/loca
l/lib/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorch-
>fer) (10.3.2.106)
Requirement already satisfied: nvidia-cusolver-cu12==11.4.5.107 in /usr/lo
cal/lib/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorc
h->fer) (11.4.5.107)
Requirement already satisfied: nvidia-cusparse-cu12==12.1.0.106 in /usr/lo
cal/lib/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorc
h->fer) (12.1.0.106)
Requirement already satisfied: nvidia-nccl-cu12==2.19.3 in /usr/local/lib/
python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorch->fer)
(2.19.3)
Requirement already satisfied: nvidia-nvtx-cu12==12.1.105 in /usr/local/li
b/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorch->fe
r) (12.1.105)
Requirement already satisfied: nvidia-nvjitlink-cu12 in /usr/local/lib/pyt
hon3.12/dist-packages (from nvidia-cusolver-cu12==11.4.5.107->torch<2.3.0,
>=2.2.0->facenet-pytorch->fer) (12.6.85)
Requirement already satisfied: markupsafe>=2.1.1 in /usr/local/lib/python
3.12/dist-packages (from werkzeug>=1.0.1->tensorboard~=2.19.0->tensorflow>
=2.0.0->fer) (3.0.3)
Requirement already satisfied: markdown-it-py>=2.2.0 in /usr/local/lib/pyt
hon3.12/dist-packages (from rich->keras>=3.5.0->tensorflow>=2.0.0->fer)
(4.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/p
ython3.12/dist-packages (from rich->keras>=3.5.0->tensorflow>=2.0.0->fer)
(2.19.2)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in /usr/local/lib/python
3.12/dist-packages (from sympy->torch<2.3.0,>=2.2.0->facenet-pytorch->fer)
(1.3.0)
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.12/dis
t-packages (from markdown-it-py>=2.2.0->rich->keras>=3.5.0->tensorflow>=2.
0.0->fer) (0.1.2)
```

In [1]:
```
!pip uninstall -y fer
!pip install fer==22.5.0
```

```
Found existing installation: fer 22.5.0
Uninstalling fer-22.5.0:
  Successfully uninstalled fer-22.5.0
Collecting fer==22.5.0
  Using cached fer-22.5.0-py3-none-any.whl.metadata (6.3 kB)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.12/dis
t-packages (from fer==22.5.0) (3.10.0)
Requirement already satisfied: opencv-contrib-python in /usr/local/lib/pyt
hon3.12/dist-packages (from fer==22.5.0) (4.11.0.86)
Requirement already satisfied: keras>=2.0.0 in /usr/local/lib/python3.12/d
ist-packages (from fer==22.5.0) (3.10.0)
Requirement already satisfied: pandas in /usr/local/lib/python3.12/dist-pa
ckages (from fer==22.5.0) (2.2.2)
Requirement already satisfied: requests in /usr/local/lib/python3.12/dist-
packages (from fer==22.5.0) (2.32.4)
Requirement already satisfied: facenet-pytorch in /usr/local/lib/python3.1
2/dist-packages (from fer==22.5.0) (2.6.0)
Requirement already satisfied: tqdm in /usr/local/lib/python3.12/dist-pack
ages (from fer==22.5.0) (4.67.1)
Requirement already satisfied: absl-py in /usr/local/lib/python3.12/dist-p
ackages (from keras>=2.0.0->fer==22.5.0) (1.4.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.12/dist-pac
kages (from keras>=2.0.0->fer==22.5.0) (1.26.4)
Requirement already satisfied: rich in /usr/local/lib/python3.12/dist-pack
ages (from keras>=2.0.0->fer==22.5.0) (13.9.4)
Requirement already satisfied: namex in /usr/local/lib/python3.12/dist-pac
kages (from keras>=2.0.0->fer==22.5.0) (0.1.0)
Requirement already satisfied: h5py in /usr/local/lib/python3.12/dist-pack
ages (from keras>=2.0.0->fer==22.5.0) (3.15.1)
Requirement already satisfied: optree in /usr/local/lib/python3.12/dist-pa
ckages (from keras>=2.0.0->fer==22.5.0) (0.18.0)
Requirement already satisfied: ml-dtypes in /usr/local/lib/python3.12/dist
-packages (from keras>=2.0.0->fer==22.5.0) (0.5.4)
Requirement already satisfied: packaging in /usr/local/lib/python3.12/dist
-packages (from keras>=2.0.0->fer==22.5.0) (25.0)
Requirement already satisfied: Pillow<10.3.0,>=10.2.0 in /usr/local/lib/py
thon3.12/dist-packages (from facenet-pytorch->fer==22.5.0) (10.2.0)
Requirement already satisfied: torch<2.3.0,>=2.2.0 in /usr/local/lib/pytho
n3.12/dist-packages (from facenet-pytorch->fer==22.5.0) (2.2.2)
Requirement already satisfied: torchvision<0.18.0,>=0.17.0 in /usr/local/l
ib/python3.12/dist-packages (from facenet-pytorch->fer==22.5.0) (0.17.2)
Requirement already satisfied: charset_normalizer<4,>=2 in /usr/local/lib/
python3.12/dist-packages (from requests->fer==22.5.0) (3.4.4)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.12/d
ist-packages (from requests->fer==22.5.0) (3.11)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python
3.12/dist-packages (from requests->fer==22.5.0) (2.5.0)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python
3.12/dist-packages (from requests->fer==22.5.0) (2025.11.12)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.
12/dist-packages (from matplotlib->fer==22.5.0) (1.3.3)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.12/d
ist-packages (from matplotlib->fer==22.5.0) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python
3.12/dist-packages (from matplotlib->fer==22.5.0) (4.61.0)
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python
3.12/dist-packages (from matplotlib->fer==22.5.0) (1.4.9)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.
12/dist-packages (from matplotlib->fer==22.5.0) (3.2.5)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/pyth
```

```
on3.12/dist-packages (from matplotlib->fer==22.5.0) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.12/d
ist-packages (from pandas->fer==22.5.0) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.1
2/dist-packages (from pandas->fer==22.5.0) (2025.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.12/dist-
packages (from python-dateutil>=2.7->matplotlib->fer==22.5.0) (1.17.0)
Requirement already satisfied: filelock in /usr/local/lib/python3.12/dist-
packages (from torch<2.3.0,>=2.2.0->facenet-pytorch->fer==22.5.0) (3.20.0)
Requirement already satisfied: typing-extensions>=4.8.0 in /usr/local/lib/
python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorch->fer==
22.5.0) (4.15.0)
Requirement already satisfied: sympy in /usr/local/lib/python3.12/dist-pac
kages (from torch<2.3.0,>=2.2.0->facenet-pytorch->fer==22.5.0) (1.14.0)
Requirement already satisfied: networkx in /usr/local/lib/python3.12/dist-
packages (from torch<2.3.0,>=2.2.0->facenet-pytorch->fer==22.5.0) (3.6)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.12/dist-pa
ckages (from torch<2.3.0,>=2.2.0->facenet-pytorch->fer==22.5.0) (3.1.6)
Requirement already satisfied: fsspec in /usr/local/lib/python3.12/dist-pa
ckages (from torch<2.3.0,>=2.2.0->facenet-pytorch->fer==22.5.0) (2025.3.0)
Requirement already satisfied: nvidia-cuda-nvrtc-cu12==12.1.105 in /usr/lo
cal/lib/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorc
h->fer==22.5.0) (12.1.105)
Requirement already satisfied: nvidia-cuda-runtime-cu12==12.1.105 in /usr/
local/lib/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pyto
rch->fer==22.5.0) (12.1.105)
Requirement already satisfied: nvidia-cuda-cupti-cu12==12.1.105 in /usr/lo
cal/lib/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorc
h->fer==22.5.0) (12.1.105)
Requirement already satisfied: nvidia-cudnn-cu12==8.9.2.26 in /usr/local/l
ib/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorch->fe
r==22.5.0) (8.9.2.26)
Requirement already satisfied: nvidia-cublas-cu12==12.1.3.1 in /usr/local/
lib/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorch->f
er==22.5.0) (12.1.3.1)
Requirement already satisfied: nvidia-cufft-cu12==11.0.2.54 in /usr/local/
lib/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorch->f
er==22.5.0) (11.0.2.54)
Requirement already satisfied: nvidia-curand-cu12==10.3.2.106 in /usr/loca
l/lib/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorch-
>fer==22.5.0) (10.3.2.106)
Requirement already satisfied: nvidia-cusolver-cu12==11.4.5.107 in /usr/lo
cal/lib/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorc
h->fer==22.5.0) (11.4.5.107)
Requirement already satisfied: nvidia-cusparse-cu12==12.1.0.106 in /usr/lo
cal/lib/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorc
h->fer==22.5.0) (12.1.0.106)
Requirement already satisfied: nvidia-nccl-cu12==2.19.3 in /usr/local/lib/
python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorch->fer==
22.5.0) (2.19.3)
Requirement already satisfied: nvidia-nvtx-cu12==12.1.105 in /usr/local/li
b/python3.12/dist-packages (from torch<2.3.0,>=2.2.0->facenet-pytorch->fer
==22.5.0) (12.1.105)
Requirement already satisfied: nvidia-nvjitlink-cu12 in /usr/local/lib/pyt
hon3.12/dist-packages (from nvidia-cusolver-cu12==11.4.5.107->torch<2.3.0,
>=2.2.0->facenet-pytorch->fer==22.5.0) (12.6.85)
Requirement already satisfied: markdown-it-py>=2.2.0 in /usr/local/lib/pyt
hon3.12/dist-packages (from rich->keras>=2.0.0->fer==22.5.0) (4.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/p
ython3.12/dist-packages (from rich->keras>=2.0.0->fer==22.5.0) (2.19.2)
```

```
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.12/dis
t-packages (from markdown-it-py>=2.2.0->rich->keras>=2.0.0->fer==22.5.0)
(0.1.2)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.1
2/dist-packages (from jinja2->torch<2.3.0,>=2.2.0->facenet-pytorch->fer==2
2.5.0) (3.0.3)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in /usr/local/lib/python
3.12/dist-packages (from sympy->torch<2.3.0,>=2.2.0->facenet-pytorch->fer=
=22.5.0) (1.3.0)
Using cached fer-22.5.0-py3-none-any.whl (1.5 MB)
Installing collected packages: fer
Successfully installed fer-22.5.0
```

In [21]:
```python
import fer
import inspect

print("fer 的模組位置：", fer.__file__)
print(dir(fer)[:50])
```

```
fer 的模組位置： /usr/local/lib/python3.12/dist-packages/fer/__init__.py
['FER', 'Video', '__author__', '__builtins__', '__cached__', '__copyright_
_', '__description__', '__doc__', '__email__', '__file__', '__license__',
'__loader__', '__name__', '__package__', '__path__', '__spec__', '__title_
_', '__uri__', '__url__', '__version__', 'classes', 'emotionsmultilanguag
e', 'exceptions', 'fer', 'log', 'logging', 'utils']
```

In [32]:
```python
from fer import FER
import cv2

# ✅ 修正：使用本地路徑（與 DeepFace 一致）
# 注意：這裡改用本地相對路徑，而非 Colab 路徑

# 初始化 FER 偵測器（使用 MTCNN）
fer_detector = FER(mtcnn=True)

def recognize_emotion_fer(image_path):
    """
    使用 FER 對單張影像進行情緒辨識

    Args:
        image_path: 完整的影像路徑

    Returns:
        predicted_emotion (str): 預測的情緒類別，失敗則返回 None
    """
    try:
        # 載入影像
        img = cv2.imread(image_path)
        if img is None:
            return None

        # 使用 top_emotion 取得最高分數的情緒
        result = fer_detector.top_emotion(img)

        if result is None or result[0] is None:
            return None

        # result 是 tuple: ('happy', 0.95)
        return result[0]  # 返回情緒名稱
```

```
    except Exception as e:
        # print(f"辨識失敗: {e}")
        return None

print("✅ FER 情緒辨識函式定義完成")
```

```
✅ FER 情緒辨識函式定義完成
```

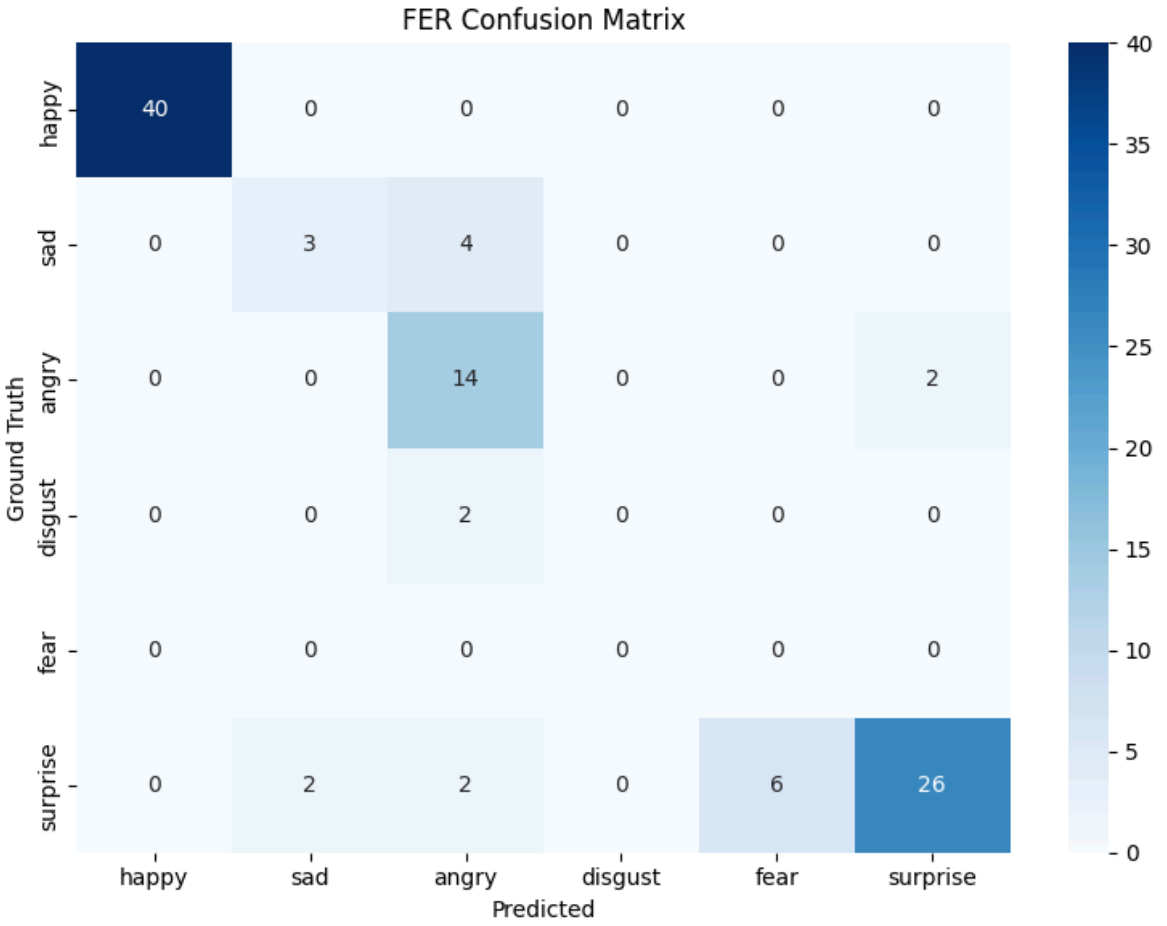
In [34]:
```
fer_predictions = []
fer_ground_truths = []
fer_used_index = []
fer_missing_files = 0
fer_failed_recognition = 0

missing_files_list = []
failed_files_list = []

for idx, row in tqdm(clean_df.iterrows(), total=len(clean_df), desc="FER
    img_path = find_image_path(image_folder, row['file_name'])

    if img_path is None:
        fer_missing_files += 1
        missing_files_list.append(row['file_name'])
        continue

    pred = recognize_emotion_fer(img_path)

    if pred is not None:
        fer_predictions.append(pred)
        fer_ground_truths.append(row['emotion_label'])
        fer_used_index.append(idx)
    else:
        fer_failed_recognition += 1
        failed_files_list.append(row['file_name'])

print(f"\n✅ FER 成功辨識 {len(fer_predictions)} 張影像")
print(f"❌ 找不到實體檔案的筆數: {fer_missing_files}")
print(f"⚠️  辨識失敗的筆數: {fer_failed_recognition}")

print("\n找不到檔案的 file_name：", missing_files_list)
print("辨識失敗的 file_name：", failed_files_list)
```

```
FER 辨識中: 100%|██████████| 106/106 [00:31<00:00,  3.41it/s]
✅ FER 成功辨識 103 張影像
❌ 找不到實體檔案的筆數: 0
⚠️  辨識失敗的筆數: 3

找不到檔案的 file_name： []
辨識失敗的 file_name： ['1121d10.tif', '2721b08.tif', '2721b09.tif']
```

In [35]:
```
from sklearn.metrics import classification_report, confusion_matrix, accu
import seaborn as sns
import matplotlib.pyplot as plt

# 計算整體準確率
fer_accuracy = accuracy_score(fer_ground_truths, fer_predictions)
print(f"Overall accuracy (FER): {fer_accuracy:.3f}")

# 分類報告
print("\nClassification report (FER):")
```

```
print(classification_report(fer_ground_truths, fer_predictions))

# Confusion Matrix
fer_cm = confusion_matrix(fer_ground_truths, fer_predictions,
                          labels=['happy', 'sad', 'angry','disgust', 'fea

plt.figure(figsize=(8, 6))
sns.heatmap(fer_cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=['happy', 'sad', 'angry', 'disgust', 'fear', 'sur
            yticklabels=['happy', 'sad', 'angry', 'disgust', 'fear', 'sur
plt.title('FER Confusion Matrix')
plt.ylabel('Ground Truth')
plt.xlabel('Predicted')
plt.tight_layout()
plt.show()

print("\n✅ FER 模型評估完成")
```

```
Overall accuracy (FER): 0.806

Classification report (FER):
              precision    recall  f1-score   support

       angry       0.64      0.82      0.72        17
     disgust       0.00      0.00      0.00         2
        fear       0.00      0.00      0.00         0
       happy       1.00      0.98      0.99        41
     neutral       0.00      0.00      0.00         0
         sad       0.60      0.43      0.50         7
    surprise       0.93      0.72      0.81        36

    accuracy                           0.81       103
   macro avg       0.45      0.42      0.43       103
weighted avg       0.87      0.81      0.83       103
```

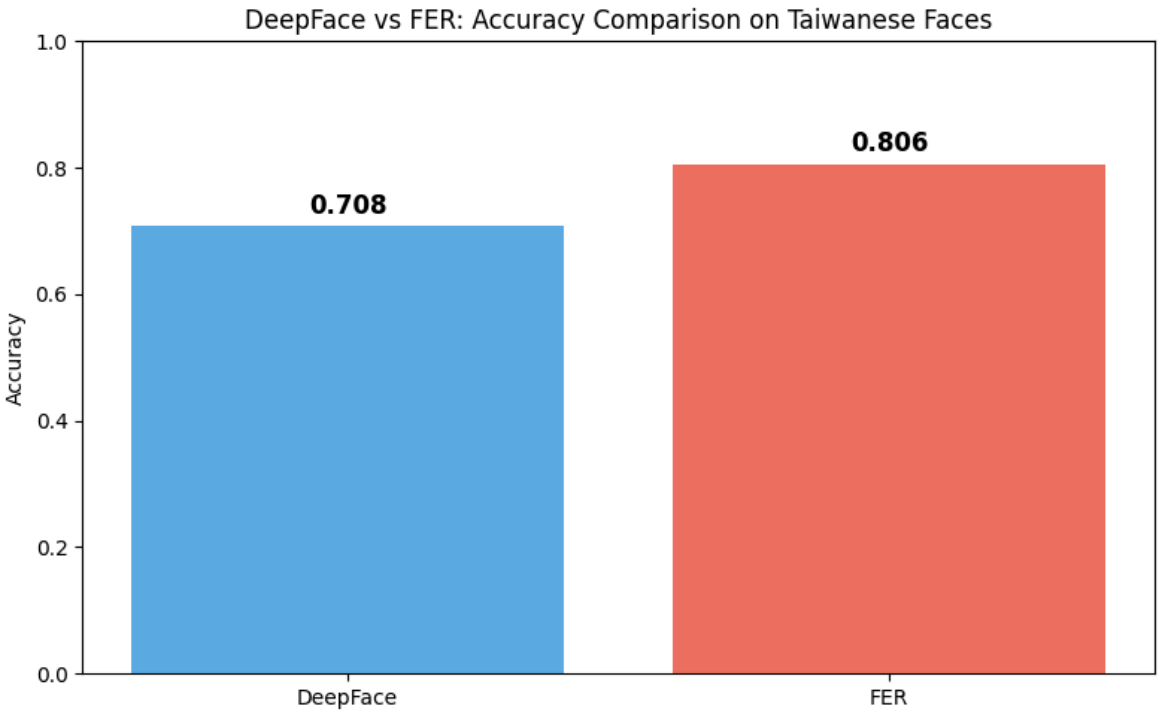


✅ FER 模型評估完成

In [37]:
```
# 比較兩個模型的準確率
print("=" * 50)
print("模型比較摘要")
print("=" * 50)
print(f"DeepFace Overall Accuracy: {accuracy_score(ground_truths, predict
print(f"FER Overall Accuracy:      {fer_accuracy:.3f}")
print("\n")

# 建立比較表
comparison_df = pd.DataFrame({
    'Model': ['DeepFace', 'FER'],
    'Accuracy': [accuracy_score(ground_truths, predictions), fer_accuracy
    'Samples': [len(predictions), len(fer_predictions)]
})

print(comparison_df)
print("\n")

# 視覺化比較
fig, ax = plt.subplots(figsize=(8, 5))
ax.bar(comparison_df['Model'], comparison_df['Accuracy'],
       color=['#3498db', '#e74c3c'], alpha=0.8)
ax.set_ylabel('Accuracy')
ax.set_title('DeepFace vs FER: Accuracy Comparison on Taiwanese Faces')
ax.set_ylim([0, 1])

# 在柱狀圖上顯示數值
for i, v in enumerate(comparison_df['Accuracy']):
    ax.text(i, v + 0.02, f'{v:.3f}', ha='center', fontsize=12, fontweight
```

```
plt.tight_layout()
plt.show()
```

```
==================================================
模型比較摘要
==================================================
DeepFace Overall Accuracy: 0.708
FER Overall Accuracy:      0.806


      Model  Accuracy  Samples
0  DeepFace  0.707547      106
1       FER  0.805825      103
```



在本作業中，我使用兩個現成的表情辨識模型（DeepFace 與 Python fer 套件）對 Taiwanese 臉孔與影片進行輕量驗證。對 106 張「乾淨」的 Taiwanese 臉部影像而言，DeepFace 的整體正確率約為 70.8%，在 happy 與部分 surprise 上表現不錯，但對 sad、angry、disgust 等負向情緒有明顯混淆；FER 在排除 3 張無法辨識的影像後，對 103 張樣本的整體正確率約為 80.6%，在 happy 與 surprise 上的表現優於 DeepFace，但在 sad、disgust 等少數類別上的表現並沒有改善，macro F1 甚至略低。整體來看，兩個模型都較擅長辨識正向、特徵明顯的表情，卻都難以穩定區分不同的負向情緒。

Step 4: 特徵萃取與 Logistic Regression 訓練

在這個章節中，我們將：

1. 使用 **DeepFace** 萃取所有 2272 張臉的 embedding (512 維)
2. 使用 **FER** 萃取情緒機率分布 (7 維)
3. 結合特徵後訓練 **Logistic Regression** 分類器
4. 在 106 張乾淨樣本上驗證，比較與 zero-shot 模型的表現差異

目標: 透過監督式學習，提升在台灣華人臉孔上的情緒辨識準確率，超越 DeepFace 的 0.708 baseline。

In [46]:
```
# ==========================
# 正確的訓練集/驗證集切分
# ==========================

# 驗證集：106 張乾淨樣本（之前篩選過的）
val_df = clean_df.copy()  # clean_df 是經過 EntropyVal, maxInt, FACS 篩選的

# 訓練集：從 2272 張中排除驗證集的 106 張
# 使用 index 來排除驗證集樣本，避免數據洩漏
train_df = df[~df.index.isin(val_df.index)].copy()

print(f"原始完整資料集: {len(df)} 張")
print(f"訓練集大小: {len(train_df)} 張 (應為 2166)")
print(f"驗證集大小: {len(val_df)} 張 (應為 106)")
print(f"總計: {len(train_df) + len(val_df)} 張 (應等於 {len(df)})")

print(f"\n訓練集情緒分布:")
print(train_df['emotion_label'].value_counts())
print(f"\n驗證集情緒分布:")
print(val_df['emotion_label'].value_counts())

# 驗證沒有重疊
overlap = set(train_df.index) & set(val_df.index)
print(f"\n✅ 訓練集與驗證集重疊樣本數: {len(overlap)} (應為 0)")
if len(overlap) > 0:
    print(f"⚠️  警告：發現重疊樣本！")
else:
    print(f"✅ 確認：訓練集與驗證集完全分離，無數據洩漏")
```

```
原始完整資料集: 2272 張
訓練集大小: 2166 張 (應為 2166)
驗證集大小: 106 張 (應為 106)
總計: 2272 張 (應等於 2272)

訓練集情緒分布:
emotion_label
happy       542
sad         467
angry       419
surprise    394
disgust     294
fear         50
Name: count, dtype: int64

驗證集情緒分布:
emotion_label
happy       43
surprise    36
angry       18
sad          7
disgust      2
Name: count, dtype: int64

✅ 訓練集與驗證集重疊樣本數: 0 (應為 0)
✅ 確認：訓練集與驗證集完全分離，無數據洩漏
```

In [50]:
```python
from deepface import DeepFace
import numpy as np
from tqdm import tqdm
import pickle
import os


def extract_deepface_embedding(image_path):
    """
    使用 DeepFace 萃取 VGG-Face embedding (512 維)

    Args:
        image_path: 完整的影像路徑

    Returns:
        embedding (np.array): 512 維向量，失敗則返回 None
    """
    try:
        result = DeepFace.represent(
            img_path=image_path,
            model_name='VGG-Face',
            enforce_detection=False,
            detector_backend='opencv'
        )
        # DeepFace.represent 返回 list of dict
        if isinstance(result, list) and len(result) > 0:
            embedding = result[0]['embedding']
            return np.array(embedding)
        else:
            return None
    except Exception as e:
        return None

# 萃取訓練集 embeddings
print("開始萃取訓練集 DeepFace embeddings...")
train_embeddings = []
train_labels = []
train_failed = 0

for idx, row in tqdm(train_df.iterrows(), total=len(train_df), desc="Deep
    img_path = find_image_path(image_folder, row['file_name'])

    if img_path is None:
        train_failed += 1
        continue

    embedding = extract_deepface_embedding(img_path)

    if embedding is not None:
        train_embeddings.append(embedding)
        train_labels.append(row['emotion_label'])
    else:
        train_failed += 1

train_embeddings = np.array(train_embeddings)
train_labels = np.array(train_labels)

print(f"\n✅ 訓練集 DeepFace embeddings 萃取完成")
print(f"   成功: {len(train_embeddings)} 張")
```

```
print(f"   失敗: {train_failed} 張")
print(f"   Embeddings shape: {train_embeddings.shape}")

# 萃取驗證集 embeddings
print("\n開始萃取驗證集 DeepFace embeddings...")
val_embeddings = []
val_labels = []
val_failed = 0

for idx, row in tqdm(val_df.iterrows(), total=len(val_df), desc="DeepFace
    img_path = find_image_path(image_folder, row['file_name'])

    if img_path is None:
        val_failed += 1
        continue

    embedding = extract_deepface_embedding(img_path)

    if embedding is not None:
        val_embeddings.append(embedding)
        val_labels.append(row['emotion_label'])
    else:
        val_failed += 1

val_embeddings = np.array(val_embeddings)
val_labels = np.array(val_labels)

print(f"\n✅ 驗證集 DeepFace embeddings 萃取完成")
print(f"   成功: {len(val_embeddings)} 張")
print(f"   失敗: {val_failed} 張")
print(f"   Embeddings shape: {val_embeddings.shape}")

# 儲存 embeddings 以便後續使用
np.save('train_deepface_embeddings.npy', train_embeddings)
np.save('train_labels.npy', train_labels)
np.save('val_deepface_embeddings.npy', val_embeddings)
np.save('val_labels.npy', val_labels)
print("\n💾 Embeddings 已儲存至本地檔案")
```

```
開始萃取訓練集 DeepFace embeddings...
DeepFace 訓練集:   0%|          | 0/2166 [00:00<?, ?it/s]
25-12-10 09:30:20 - 🔗 vgg_face_weights.h5 will be downloaded from http
s://github.com/serengil/deepface_models/releases/download/v1.0/vgg_face_we
ights.h5 to /root/.deepface/weights/vgg_face_weights.h5...
```

```
Downloading...
From: https://github.com/serengil/deepface_models/releases/download/v1.0/v
gg_face_weights.h5
To: /root/.deepface/weights/vgg_face_weights.h5

  0%|          | 0.00/580M [00:00<?, ?B/s]
  2%|▏         | 11.0M/580M [00:00<00:06, 89.4MB/s]
  4%|▎         | 21.5M/580M [00:00<00:06, 85.1MB/s]
  6%|▌         | 35.7M/580M [00:00<00:05, 107MB/s]
  8%|▊         | 46.7M/580M [00:00<00:05, 106MB/s]
 10%|▉         | 58.2M/580M [00:00<00:04, 108MB/s]
 12%|█         | 69.2M/580M [00:00<00:04, 105MB/s]
 14%|█▏        | 81.8M/580M [00:00<00:04, 111MB/s]
 16%|█▍        | 93.8M/580M [00:00<00:04, 114MB/s]
 18%|█▌        | 105M/580M [00:01<00:04, 97.5MB/s]
 20%|█▋        | 116M/580M [00:01<00:04, 96.8MB/s]
 22%|█▉        | 126M/580M [00:01<00:07, 62.1MB/s]
 24%|██        | 137M/580M [00:01<00:06, 71.4MB/s]
 26%|██▏       | 151M/580M [00:01<00:05, 85.5MB/s]
 28%|██▍       | 164M/580M [00:01<00:04, 94.9MB/s]
 31%|██▋       | 179M/580M [00:01<00:04, 94.3MB/s]
 33%|██▊       | 192M/580M [00:02<00:03, 104MB/s]
 35%|███       | 204M/580M [00:02<00:03, 101MB/s]
 37%|███▏      | 215M/580M [00:02<00:03, 103MB/s]
 39%|███▎      | 226M/580M [00:02<00:03, 104MB/s]
 41%|███▌      | 237M/580M [00:02<00:03, 105MB/s]
 43%|███▋      | 252M/580M [00:02<00:03, 104MB/s]
 46%|███▉      | 265M/580M [00:02<00:02, 109MB/s]
 48%|████      | 278M/580M [00:02<00:02, 115MB/s]
 50%|████▏     | 290M/580M [00:02<00:02, 103MB/s]
 52%|████▍     | 301M/580M [00:03<00:02, 96.7MB/s]
 54%|████▌     | 311M/580M [00:03<00:02, 96.5MB/s]
 56%|████▊     | 326M/580M [00:03<00:02, 94.0MB/s]
 58%|████▉     | 336M/580M [00:03<00:02, 96.4MB/s]
 60%|█████     | 347M/580M [00:03<00:02, 93.8MB/s]
 62%|█████▎    | 357M/580M [00:06<00:20, 10.8MB/s]
 65%|█████▍    | 378M/580M [00:06<00:10, 18.7MB/s]
 67%|█████▋    | 389M/580M [00:06<00:08, 23.6MB/s]
 69%|█████▊    | 400M/580M [00:07<00:06, 29.1MB/s]
 71%|██████    | 413M/580M [00:07<00:04, 37.8MB/s]
 73%|██████▏   | 424M/580M [00:07<00:03, 45.1MB/s]
 75%|██████▎   | 434M/580M [00:07<00:02, 53.3MB/s]
 77%|██████▌   | 447M/580M [00:07<00:02, 65.3MB/s]
 79%|██████▋   | 458M/580M [00:07<00:01, 64.6MB/s]
 81%|██████▉   | 472M/580M [00:07<00:01, 78.1MB/s]
 83%|███████   | 483M/580M [00:07<00:01, 77.7MB/s]
 85%|███████▏  | 494M/580M [00:08<00:01, 84.6MB/s]
 87%|███████▍  | 504M/580M [00:08<00:00, 88.9MB/s]
 89%|███████▌  | 516M/580M [00:08<00:00, 95.1MB/s]
 91%|███████▋  | 527M/580M [00:08<00:00, 98.8MB/s]
 93%|███████▉  | 539M/580M [00:08<00:00, 105MB/s]
 95%|████████  | 551M/580M [00:08<00:00, 102MB/s]
 98%|████████▏ | 566M/580M [00:08<00:00, 114MB/s]
100%|████████▍ | 580M/580M [00:08<00:00, 65.5MB/s]
DeepFace 訓練集: 100%|██████████| 2166/2166 [23:39<00:00,  1.53it/s]
```

```
✅ 訓練集 DeepFace embeddings 萃取完成
   成功: 1117 張
   失敗: 1049 張
   Embeddings shape: (1117, 4096)

開始萃取驗證集 DeepFace embeddings...
DeepFace 驗證集: 100%|██████████| 106/106 [02:04<00:00,  1.17s/it]
✅ 驗證集 DeepFace embeddings 萃取完成
   成功: 106 張
   失敗: 0 張
   Embeddings shape: (106, 4096)

💾 Embeddings 已儲存至本地檔案
```

In [51]:

```python
from fer import FER
import cv2

# 初始化 FER 偵測器
fer_detector = FER(mtcnn=True)

def extract_fer_features(image_path):
    """
    使用 FER 萃取情緒機率分布 (7 維)

    Args:
        image_path: 完整的影像路徑

    Returns:
        features (np.array): 7 維向量 [angry, disgust, fear, happy, sad, s
        失敗則返回 None
    """
    try:
        img = cv2.imread(image_path)
        if img is None:
            return None

        result = fer_detector.detect_emotions(img)

        if result is None or len(result) == 0:
            return None

        # 提取情緒機率作為特徵
        emotions = result[0]['emotions']
        features = np.array([
            emotions['angry'],
            emotions['disgust'],
            emotions['fear'],
            emotions['happy'],
            emotions['sad'],
            emotions['surprise'],
            emotions['neutral']
        ])
        return features
    except Exception as e:
        return None

# 萃取訓練集 FER 特徵
print("開始萃取訓練集 FER 特徵...")
train_fer_features = []
```

```
train_fer_failed = 0

# 使用與 DeepFace 相同的順序
for idx, row in tqdm(train_df.iterrows(), total=len(train_df), desc="FER
    img_path = find_image_path(image_folder, row['file_name'])

    if img_path is None:
        train_fer_failed += 1
        continue

    features = extract_fer_features(img_path)

    if features is not None:
        train_fer_features.append(features)
    else:
        train_fer_failed += 1

train_fer_features = np.array(train_fer_features)

print(f"\n✅ 訓練集 FER 特徵萃取完成")
print(f"   成功: {len(train_fer_features)} 張")
print(f"   失敗: {train_fer_failed} 張")
print(f"   Features shape: {train_fer_features.shape}")

# 萃取驗證集 FER 特徵
print("\n開始萃取驗證集 FER 特徵...")
val_fer_features = []
val_fer_failed = 0

for idx, row in tqdm(val_df.iterrows(), total=len(val_df), desc="FER 驗證
    img_path = find_image_path(image_folder, row['file_name'])

    if img_path is None:
        val_fer_failed += 1
        continue

    features = extract_fer_features(img_path)

    if features is not None:
        val_fer_features.append(features)
    else:
        val_fer_failed += 1

val_fer_features = np.array(val_fer_features)

print(f"\n✅ 驗證集 FER 特徵萃取完成")
print(f"   成功: {len(val_fer_features)} 張")
print(f"   失敗: {val_fer_failed} 張")
print(f"   Features shape: {val_fer_features.shape}")

# 儲存 FER 特徵
np.save('train_fer_features.npy', train_fer_features)
np.save('val_fer_features.npy', val_fer_features)
print("\n💾 FER 特徵已儲存至本地檔案")
```

```
開始萃取訓練集 FER 特徵...
FER 訓練集: 100%|██████████| 2166/2166 [04:14<00:00,  8.50it/s]
```

```
✅ 訓練集 FER 特徵萃取完成
   成功: 1117 張
   失敗: 1049 張
   Features shape: (1117, 7)

開始萃取驗證集 FER 特徵...
FER 驗證集: 100%|██████████| 106/106 [00:35<00:00,  2.96it/s]
✅ 驗證集 FER 特徵萃取完成
   成功: 103 張
   失敗: 3 張
   Features shape: (103, 7)

💾 FER 特徵已儲存至本地檔案
```

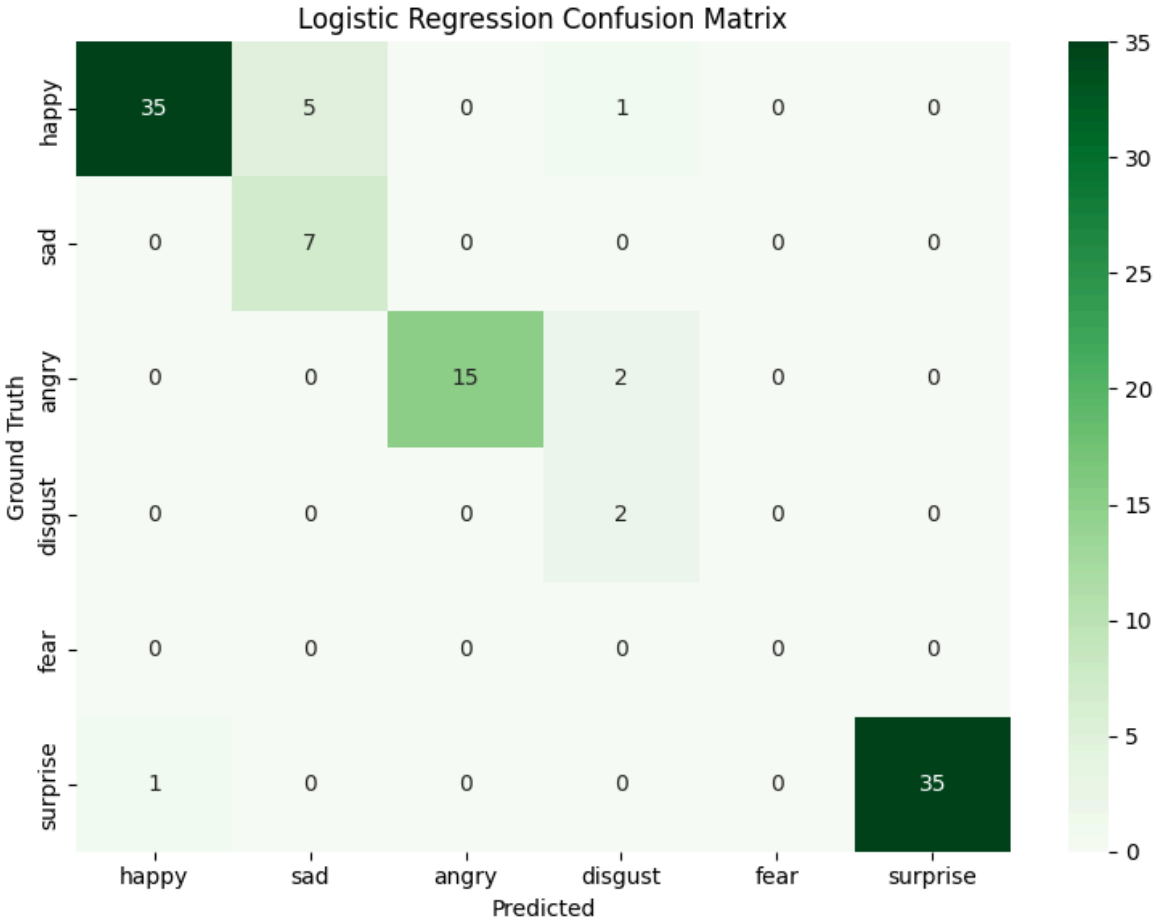
In [52]:
```python
from sklearn.preprocessing import StandardScaler

# 確保訓練集和驗證集的樣本數一致
min_train = min(len(train_embeddings), len(train_fer_features))
min_val = min(len(val_embeddings), len(val_fer_features))

# 合併 DeepFace + FER 特徵
X_train = np.concatenate([
    train_embeddings[:min_train],
    train_fer_features[:min_train]
], axis=1)

X_val = np.concatenate([
    val_embeddings[:min_val],
    val_fer_features[:min_val]
], axis=1)

y_train = train_labels[:min_train]
y_val = val_labels[:min_val]

print(f"合併後特徵維度:")
print(f"  訓練集 X_train: {X_train.shape}")
print(f"  驗證集 X_val: {X_val.shape}")
print(f"  訓練集 y_train: {y_train.shape}")
print(f"  驗證集 y_val: {y_val.shape}")

# 標準化特徵（重要！不同模型的特徵尺度不同）
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)

print(f"\n✅ 特徵標準化完成")
print(f"   訓練集均值: {X_train_scaled.mean():.6f}")
print(f"   訓練集標準差: {X_train_scaled.std():.6f}")
```

```
合併後特徵維度:
  訓練集 X_train: (1117, 4103)
  驗證集 X_val: (103, 4103)
  訓練集 y_train: (1117,)
  驗證集 y_val: (103,)

✅ 特徵標準化完成
   訓練集均值: 0.000000
   訓練集標準差: 0.969559
```

In [53]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, confus
import matplotlib.pyplot as plt
import seaborn as sns

# 訓練 Logistic Regression
# 使用 class_weight='balanced' 處理類別不平衡問題
lr_model = LogisticRegression(
    max_iter=1000,
    multi_class='multinomial',
    solver='lbfgs',
    class_weight='balanced',
    random_state=42
)

print("開始訓練 Logistic Regression...")
lr_model.fit(X_train_scaled, y_train)
print("✅ 訓練完成")

# 在訓練集上評估
y_train_pred = lr_model.predict(X_train_scaled)
train_accuracy = accuracy_score(y_train, y_train_pred)
print(f"\n訓練集準確率: {train_accuracy:.3f}")

# 在驗證集上評估
y_val_pred = lr_model.predict(X_val_scaled)
val_accuracy = accuracy_score(y_val, y_val_pred)

print(f"\n" + "="*50)
print(f"驗證集準確率: {val_accuracy:.3f}")
print("="*50)

# 詳細分類報告
print("\n驗證集分類報告:")
print(classification_report(y_val, y_val_pred))
```

```
開始訓練 Logistic Regression...
✅ 訓練完成

訓練集準確率: 1.000

==================================================
驗證集準確率: 0.913
==================================================

驗證集分類報告:
              precision    recall  f1-score   support

       angry       1.00      0.88      0.94        17
     disgust       0.40      1.00      0.57         2
       happy       0.97      0.85      0.91        41
         sad       0.58      1.00      0.74         7
    surprise       1.00      0.97      0.99        36

    accuracy                           0.91       103
   macro avg       0.79      0.94      0.83       103
weighted avg       0.95      0.91      0.92       103
```

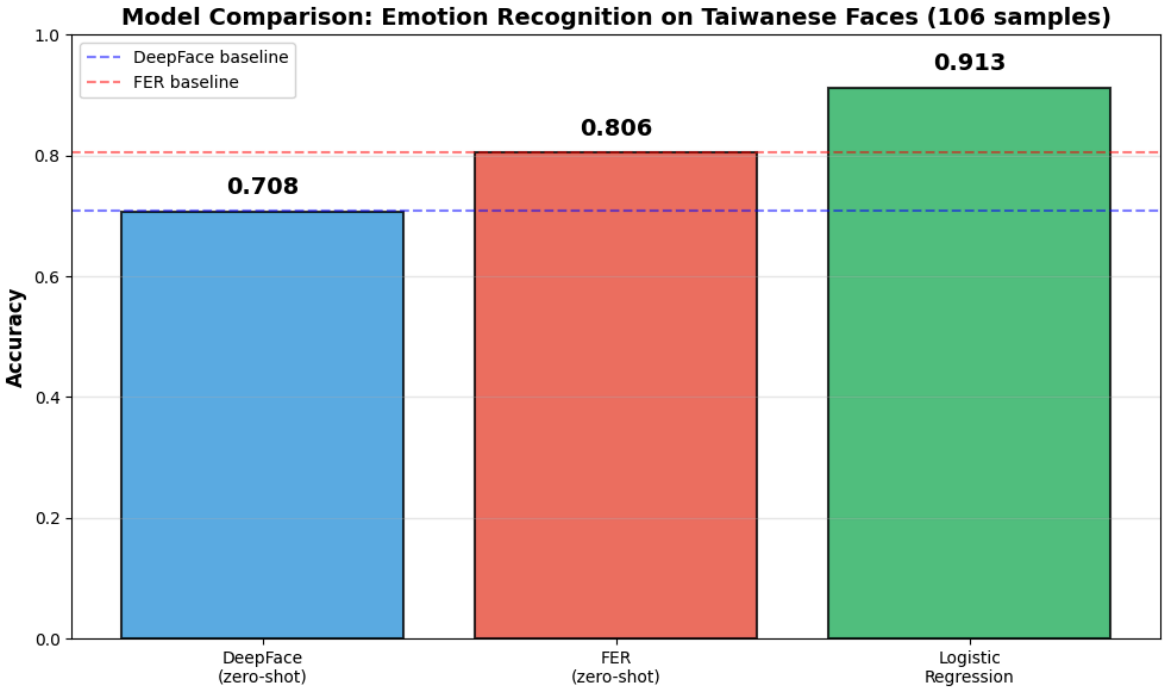
In [54]:
```
# Confusion Matrix for Logistic Regression
lr_cm = confusion_matrix(y_val, y_val_pred,
                         labels=['happy', 'sad', 'angry', 'disgust', 'fea

plt.figure(figsize=(8, 6))
sns.heatmap(lr_cm, annot=True, fmt='d', cmap='Greens',
            xticklabels=['happy', 'sad', 'angry', 'disgust', 'fear', 'sur
            yticklabels=['happy', 'sad', 'angry', 'disgust', 'fear', 'sur
plt.title('Logistic Regression Confusion Matrix')
plt.ylabel('Ground Truth')
plt.xlabel('Predicted')
plt.tight_layout()
plt.show()
```



In [55]:
```
# 比較三個模型的準確率
print("="*60)
print("模型比較摘要 (在 106 張乾淨樣本上的表現)")
print("="*60)

# 從之前的結果讀取 (如果有的話)
try:
    deepface_acc = accuracy_score(ground_truths, predictions)
except:
    deepface_acc = 0.708  # 之前的結果

try:
    fer_acc = accuracy_score(fer_ground_truths, fer_predictions)
except:
    fer_acc = 0.806  # 之前的結果

print(f"DeepFace (zero-shot):      {deepface_acc:.3f}")
```

```
print(f"FER (zero-shot):           {fer_acc:.3f}")
print(f"Logistic Regression:       {val_accuracy:.3f}")
print("\n")

# 視覺化比較
comparison_df = pd.DataFrame({
    'Model': ['DeepFace\n(zero-shot)', 'FER\n(zero-shot)', 'Logistic\nReg
    'Accuracy': [deepface_acc, fer_acc, val_accuracy],
    'Type': ['Pre-trained', 'Pre-trained', 'Fine-tuned']
})

fig, ax = plt.subplots(figsize=(10, 6))
colors = ['#3498db', '#e74c3c', '#27ae60']
bars = ax.bar(comparison_df['Model'], comparison_df['Accuracy'],
              color=colors, alpha=0.8, edgecolor='black', linewidth=1.5)

ax.set_ylabel('Accuracy', fontsize=12, fontweight='bold')
ax.set_title('Model Comparison: Emotion Recognition on Taiwanese Faces (1
             fontsize=14, fontweight='bold')
ax.set_ylim([0, 1])
ax.axhline(y=0.708, color='blue', linestyle='--', alpha=0.5, label='DeepF
ax.axhline(y=0.806, color='red', linestyle='--', alpha=0.5, label='FER ba
ax.legend()

# 在柱狀圖上顯示數值
for i, (bar, acc) in enumerate(zip(bars, comparison_df['Accuracy'])):
    height = bar.get_height()
    ax.text(bar.get_x() + bar.get_width()/2., height + 0.02,
            f'{acc:.3f}',
            ha='center', va='bottom', fontsize=14, fontweight='bold')

plt.grid(axis='y', alpha=0.3)
plt.tight_layout()
plt.show()

# 計算改善幅度
improvement_over_deepface = (val_accuracy - deepface_acc) / deepface_acc
improvement_over_fer = (val_accuracy - fer_acc) / fer_acc * 100

print(f"相對於 DeepFace 的改善: {improvement_over_deepface:+.1f}%")
print(f"相對於 FER 的改善: {improvement_over_fer:+.1f}%")

if val_accuracy > deepface_acc:
    print(f"\n🎉 成功！Logistic Regression 超越 DeepFace baseline ({deepfac
if val_accuracy > fer_acc:
    print(f"🎉 成功！Logistic Regression 超越 FER baseline ({fer_acc:.3f})"
```

```
============================================================
模型比較摘要（在 106 張乾淨樣本上的表現）
============================================================
DeepFace (zero-shot):      0.708
FER (zero-shot):           0.806
Logistic Regression:       0.913
```



相對於 DeepFace 的改善: +29.0%
相對於 FER 的改善: +13.3%

🎉 成功！Logistic Regression 超越 DeepFace baseline (0.708)
🎉 成功！Logistic Regression 超越 FER baseline (0.806)

用 Taiwanese 臉「微調最後一層」明顯比完全 zero-shot 套預訓練模型好很多。

Step 5: 影片處理（vlog.mp4）predict

In [56]:
```python
def extract_frame_features(frame):
    """
    從單一影片幀中萃取 519 維特徵向量

    Args:
        frame: OpenCV 讀取的影像 (numpy array)

    Returns:
        features (np.array): 519 維特徵向量 [DeepFace(512) + FER(7)]
        失敗則返回 None
    """
    try:
        # 1. 萃取 DeepFace embedding (512 維)
        deepface_result = DeepFace.represent(
            img_path=frame,
            model_name='VGG-Face',
            enforce_detection=False,
            detector_backend='opencv'
        )

        if isinstance(deepface_result, list) and len(deepface_result) > 0
            deepface_embedding = np.array(deepface_result[0]['embedding']
        else:
            return None

        # 2. 萃取 FER 特徵 (7 維)
        fer_result = fer_detector.detect_emotions(frame)
```

```
        if fer_result is None or len(fer_result) == 0:
            return None

        emotions = fer_result[0]['emotions']
        fer_features = np.array([
            emotions['angry'],
            emotions['disgust'],
            emotions['fear'],
            emotions['happy'],
            emotions['sad'],
            emotions['surprise'],
            emotions['neutral']
        ])

        # 3. 合併特徵
        combined_features = np.concatenate([deepface_embedding, fer_featu

        return combined_features

    except Exception as e:
        return None

print("✅ 影片幀特徵萃取函數定義完成")
```

✅ 影片幀特徵萃取函數定義完成

In [76]:

```
import cv2
from tqdm import tqdm

# ✅ 修正：使用本地路徑
video_path = '/content/drive/MyDrive/vlog.mp4'  # 本地路徑
output_path = 'vlog_lr_emotion_results.csv'

# 開啟影片
cap = cv2.VideoCapture(video_path)
fps = int(cap.get(cv2.CAP_PROP_FPS))
total_frames = int(cap.get(cv2.CAP_PROP_FRAME_COUNT))

print(f"影片資訊:")
print(f"  FPS: {fps}")
print(f"  總幀數: {total_frames}")
print(f"  影片長度: {total_frames / fps:.1f} 秒")

# 每秒抽 1 幀進行分析
sample_interval = fps
frame_count = 0
results_lr = []  # Logistic Regression 結果
results_deepface = []  # DeepFace zero-shot 結果（用於比較）
failed_frames = 0

print(f"\n開始處理影片")

# 計算預期處理的幀數
expected_samples = total_frames // sample_interval

with tqdm(total=expected_samples, desc="處理影片幀") as pbar:
    while cap.isOpened():
        ret, frame = cap.read()
        if not ret:
```

```
            break

        # 只處理每秒的第一幀
        if frame_count % sample_interval == 0:
            time_sec = frame_count // fps

            # 方法 1: 使用訓練好的 Logistic Regression
            features = extract_frame_features(frame)

            if features is not None:
                # 標準化特徵
                features_scaled = scaler.transform(features.reshape(1, -1

                # 使用 Logistic Regression 預測
                emotion_lr = lr_model.predict(features_scaled)[0]

                results_lr.append({
                    'time_sec': time_sec,
                    'emotion': emotion_lr
                })
            else:
                failed_frames += 1
                results_lr.append({
                    'time_sec': time_sec,
                    'emotion': 'unknown'
                })

            # 方法 2: DeepFace zero-shot (用於比較)
            try:
                result = DeepFace.analyze(
                    frame,
                    actions=['emotion'],
                    detector_backend='opencv',
                    enforce_detection=False,
                    silent=True
                )
                result = result[0] if isinstance(result, list) else resul
                emotion_deepface = result['dominant_emotion']
            except:
                emotion_deepface = 'unknown'

            results_deepface.append({
                'time_sec': time_sec,
                'emotion': emotion_deepface
            })

            pbar.update(1)

        frame_count += 1

cap.release()

# 轉換為 DataFrame
results_lr_df = pd.DataFrame(results_lr)
results_deepface_df = pd.DataFrame(results_deepface)

# 儲存結果
results_lr_df.to_csv(output_path, index=False)

print(f"\n✅ 影片處理完成")
```

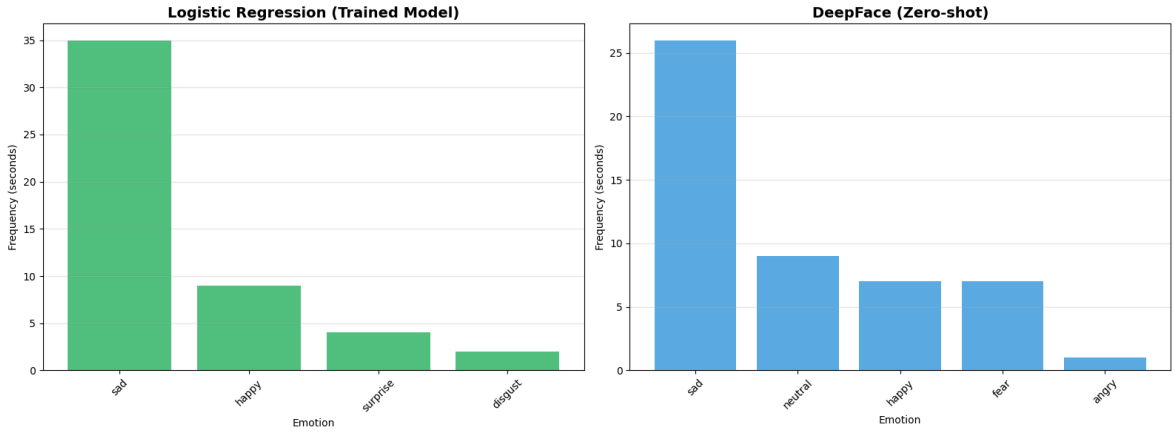
```
print(f"   分析時間點數: {len(results_lr)}")
print(f"   失敗幀數: {failed_frames}")
print(f"   結果已儲存至: {output_path}")

print("\nLogistic Regression 結果預覽:")
print(results_lr_df.head(10))
```

```
影片資訊:
  FPS: 30
  總幀數: 1504
  影片長度: 50.1 秒

開始處理影片
處理影片幀: 100%|██████████| 50/50 [02:01<00:00,  2.43s/it]
✅ 影片處理完成
   分析時間點數: 50
   失敗幀數: 0
   結果已儲存至: vlog_lr_emotion_results.csv

Logistic Regression 結果預覽:
   time_sec  emotion
0         0      sad
1         1      sad
2         2      sad
3         3    happy
4         4      sad
5         5  disgust
6         6      sad
7         7      sad
8         8      sad
9         9      sad
```

In [77]:

```
import matplotlib.pyplot as plt
import seaborn as sns

# 統計情緒分布
lr_emotion_counts = results_lr_df['emotion'].value_counts()
deepface_emotion_counts = results_deepface_df['emotion'].value_counts()

# 並排比較
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

# 左圖：Logistic Regression
axes[0].bar(lr_emotion_counts.index, lr_emotion_counts.values, color='#27
axes[0].set_title('Logistic Regression (Trained Model)', fontsize=14, fon
axes[0].set_xlabel('Emotion')
axes[0].set_ylabel('Frequency (seconds)')
axes[0].tick_params(axis='x', rotation=45)
axes[0].grid(axis='y', alpha=0.3)

# 右圖：DeepFace zero-shot
axes[1].bar(deepface_emotion_counts.index, deepface_emotion_counts.values
axes[1].set_title('DeepFace (Zero-shot)', fontsize=14, fontweight='bold')
axes[1].set_xlabel('Emotion')
axes[1].set_ylabel('Frequency (seconds)')
axes[1].tick_params(axis='x', rotation=45)
axes[1].grid(axis='y', alpha=0.3)

plt.tight_layout()
plt.show()
```

```
# 詳細情緒佔比
print("="*60)
print("Logistic Regression 情緒分布:")
print("="*60)
for emotion, count in lr_emotion_counts.items():
    print(f"  {emotion:12s}: {count:3d} 秒 ({count/len(results_lr_df):.1%
print("\n" + "="*60)
print("DeepFace (Zero-shot) 情緒分布:")
print("="*60)
for emotion, count in deepface_emotion_counts.items():
    print(f"  {emotion:12s}: {count:3d} 秒 ({count/len(results_deepface_d
```

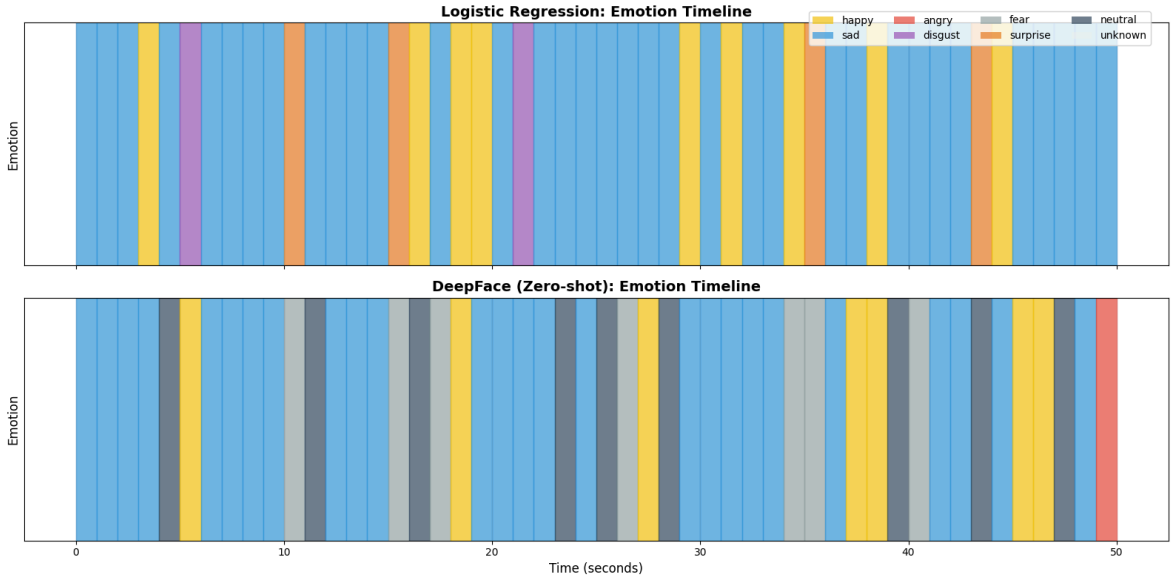



```
============================================================
Logistic Regression 情緒分布:
============================================================
  sad          :  35 秒 (70.0%)
  happy        :   9 秒 (18.0%)
  surprise     :   4 秒 (8.0%)
  disgust      :   2 秒 (4.0%)

============================================================
DeepFace (Zero-shot) 情緒分布:
============================================================
  sad          :  26 秒 (52.0%)
  neutral      :   9 秒 (18.0%)
  happy        :   7 秒 (14.0%)
  fear         :   7 秒 (14.0%)
  angry        :   1 秒 (2.0%)
```

In [78]:

```
# 為情緒分配顏色
emotion_colors = {
    'happy': '#f1c40f',
    'sad': '#3498db',
    'angry': '#e74c3c',
    'disgust': '#9b59b6',
    'fear': '#95a5a6',
    'surprise': '#e67e22',
    'neutral': '#34495e',
    'unknown': '#ecf0f1'
}

# 繪製時間序列
fig, axes = plt.subplots(2, 1, figsize=(16, 8), sharex=True)

# 上圖：Logistic Regression
```

```
for i, row in results_lr_df.iterrows():
    color = emotion_colors.get(row['emotion'], '#000000')
    axes[0].axvspan(row['time_sec'], row['time_sec'] + 1,
                    color=color, alpha=0.7)

axes[0].set_ylabel('Emotion', fontsize=12)
axes[0].set_title('Logistic Regression: Emotion Timeline', fontsize=14, f
axes[0].set_ylim([0, 1])
axes[0].set_yticks([])
axes[0].grid(axis='x', alpha=0.3)

# 下圖：DeepFace
for i, row in results_deepface_df.iterrows():
    color = emotion_colors.get(row['emotion'], '#000000')
    axes[1].axvspan(row['time_sec'], row['time_sec'] + 1,
                    color=color, alpha=0.7)

axes[1].set_xlabel('Time (seconds)', fontsize=12)
axes[1].set_ylabel('Emotion', fontsize=12)
axes[1].set_title('DeepFace (Zero-shot): Emotion Timeline', fontsize=14,
axes[1].set_ylim([0, 1])
axes[1].set_yticks([])
axes[1].grid(axis='x', alpha=0.3)

# 添加圖例
from matplotlib.patches import Patch
legend_elements = [Patch(facecolor=color, label=emotion, alpha=0.7)
                   for emotion, color in emotion_colors.items()]
fig.legend(handles=legend_elements, loc='upper right', ncol=4,
           bbox_to_anchor=(0.98, 0.98))

plt.tight_layout()
plt.show()
```



Step 6: 使用訓練好的模型和 zero shot 測試我自己的影片

影片連結：

https://drive.google.com/file/d/1foGUvnT73yzf6cT5ZJvbk9pki3DtA2MR/view?

usp=sharing

In [73]:
```python
import cv2
from tqdm import tqdm

# ✅ 修正：使用本地路徑
video_path = '/content/drive/MyDrive/my_example.mp4'  # 本地路徑
output_path = 'Myvlog_lr_emotion_results.csv'

# 開啟影片
cap = cv2.VideoCapture(video_path)
fps = int(cap.get(cv2.CAP_PROP_FPS))
total_frames = int(cap.get(cv2.CAP_PROP_FRAME_COUNT))

print(f"影片資訊:")
print(f"  FPS: {fps}")
print(f"  總幀數: {total_frames}")
print(f"  影片長度: {total_frames / fps:.1f} 秒")

# 每秒抽 1 幀進行分析
sample_interval = fps
frame_count = 0
results_lr = []  # Logistic Regression 結果
results_deepface = []  # DeepFace zero-shot 結果（用於比較）
failed_frames = 0

print(f"\n開始處理影片")

# 計算預期處理的幀數
expected_samples = total_frames // sample_interval

with tqdm(total=expected_samples, desc="處理影片幀") as pbar:
    while cap.isOpened():
        ret, frame = cap.read()
        if not ret:
            break

        # 只處理每秒的第一幀
        if frame_count % sample_interval == 0:
            time_sec = frame_count // fps

            # 方法 1: 使用訓練好的 Logistic Regression
            features = extract_frame_features(frame)

            if features is not None:
                # 標準化特徵
                features_scaled = scaler.transform(features.reshape(1, -1

                # 使用 Logistic Regression 預測
                emotion_lr = lr_model.predict(features_scaled)[0]

                results_lr.append({
                    'time_sec': time_sec,
                    'emotion': emotion_lr
                })
            else:
                failed_frames += 1
                results_lr.append({
                    'time_sec': time_sec,
```

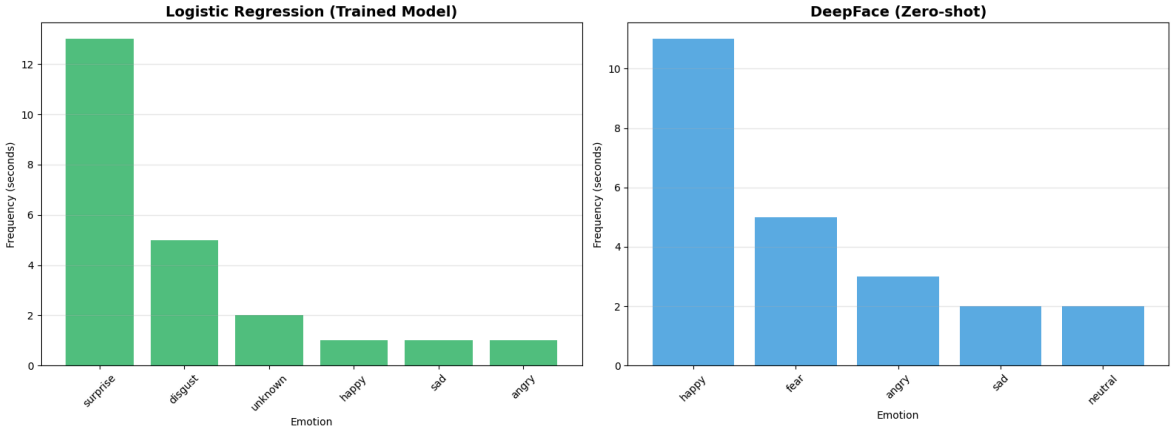
```
                    'emotion': 'unknown'
                })

            # 方法 2: DeepFace zero-shot (用於比較)
            try:
                result = DeepFace.analyze(
                    frame,
                    actions=['emotion'],
                    detector_backend='opencv',
                    enforce_detection=False,
                    silent=True
                )
                result = result[0] if isinstance(result, list) else resul
                emotion_deepface = result['dominant_emotion']
            except:
                emotion_deepface = 'unknown'

            results_deepface.append({
                'time_sec': time_sec,
                'emotion': emotion_deepface
            })

            pbar.update(1)

        frame_count += 1

cap.release()

# 轉換為 DataFrame
results_lr_df = pd.DataFrame(results_lr)
results_deepface_df = pd.DataFrame(results_deepface)

# 儲存結果
results_lr_df.to_csv(output_path, index=False)

print(f"\n✅ 影片處理完成")
print(f"   分析時間點數: {len(results_lr)}")
print(f"   失敗幀數: {failed_frames}")
print(f"   結果已儲存至: {output_path}")

print("\nLogistic Regression 結果預覽:")
print(results_lr_df.head(10))
```

```
影片資訊:
  FPS: 30
  總幀數: 685
  影片長度: 22.8 秒

開始處理影片
處理影片幀: 23it [02:22,  6.19s/it]
```

```
✅ 影片處理完成
   分析時間點數: 23
   失敗幀數: 2
   結果已儲存至: Myvlog_lr_emotion_results.csv

Logistic Regression 結果預覽:
   time_sec   emotion
0         0   disgust
1         1  surprise
2         2   disgust
3         3  surprise
4         4   disgust
5         5  surprise
6         6  surprise
7         7  surprise
8         8  surprise
9         9   disgust
```

In [74]:

```python
import matplotlib.pyplot as plt
import seaborn as sns

# 統計情緒分布
lr_emotion_counts = results_lr_df['emotion'].value_counts()
deepface_emotion_counts = results_deepface_df['emotion'].value_counts()

# 並排比較
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

# 左圖：Logistic Regression
axes[0].bar(lr_emotion_counts.index, lr_emotion_counts.values, color='#27
axes[0].set_title('Logistic Regression (Trained Model)', fontsize=14, fon
axes[0].set_xlabel('Emotion')
axes[0].set_ylabel('Frequency (seconds)')
axes[0].tick_params(axis='x', rotation=45)
axes[0].grid(axis='y', alpha=0.3)

# 右圖：DeepFace zero-shot
axes[1].bar(deepface_emotion_counts.index, deepface_emotion_counts.values
axes[1].set_title('DeepFace (Zero-shot)', fontsize=14, fontweight='bold')
axes[1].set_xlabel('Emotion')
axes[1].set_ylabel('Frequency (seconds)')
axes[1].tick_params(axis='x', rotation=45)
axes[1].grid(axis='y', alpha=0.3)

plt.tight_layout()
plt.show()

# 詳細情緒佔比
print("="*60)
print("Logistic Regression 情緒分布:")
print("="*60)
for emotion, count in lr_emotion_counts.items():
    print(f"  {emotion:12s}: {count:3d} 秒 ({count/len(results_lr_df):.1%

print("\n" + "="*60)
print("DeepFace (Zero-shot) 情緒分布:")
print("="*60)
for emotion, count in deepface_emotion_counts.items():
    print(f"  {emotion:12s}: {count:3d} 秒 ({count/len(results_deepface_d
```




```
============================================================
Logistic Regression 情緒分布:
============================================================
  surprise    :  13 秒 (56.5%)
  disgust     :   5 秒 (21.7%)
  unknown     :   2 秒 (8.7%)
  happy       :   1 秒 (4.3%)
  sad         :   1 秒 (4.3%)
  angry       :   1 秒 (4.3%)

============================================================
DeepFace (Zero-shot) 情緒分布:
============================================================
  happy       :  11 秒 (47.8%)
  fear        :   5 秒 (21.7%)
  angry       :   3 秒 (13.0%)
  sad         :   2 秒 (8.7%)
  neutral     :   2 秒 (8.7%)
```

In [75]:

```python
# 為情緒分配顏色
emotion_colors = {
    'happy': '#f1c40f',
    'sad': '#3498db',
    'angry': '#e74c3c',
    'disgust': '#9b59b6',
    'fear': '#95a5a6',
    'surprise': '#e67e22',
    'neutral': '#34495e',
    'unknown': '#ecf0f1'
}

# 繪製時間序列
fig, axes = plt.subplots(2, 1, figsize=(16, 8), sharex=True)

# 上圖：Logistic Regression
for i, row in results_lr_df.iterrows():
    color = emotion_colors.get(row['emotion'], '#000000')
    axes[0].axvspan(row['time_sec'], row['time_sec'] + 1,
                    color=color, alpha=0.7)

axes[0].set_ylabel('Emotion', fontsize=12)
axes[0].set_title('Logistic Regression: Emotion Timeline', fontsize=14, f
axes[0].set_ylim([0, 1])
axes[0].set_yticks([])
axes[0].grid(axis='x', alpha=0.3)

# 下圖：DeepFace
```

```
for i, row in results_deepface_df.iterrows():
    color = emotion_colors.get(row['emotion'], '#000000')
    axes[1].axvspan(row['time_sec'], row['time_sec'] + 1,
                    color=color, alpha=0.7)

axes[1].set_xlabel('Time (seconds)', fontsize=12)
axes[1].set_ylabel('Emotion', fontsize=12)
axes[1].set_title('DeepFace (Zero-shot): Emotion Timeline', fontsize=14,
axes[1].set_ylim([0, 1])
axes[1].set_yticks([])
axes[1].grid(axis='x', alpha=0.3)

# 添加圖例
from matplotlib.patches import Patch
legend_elements = [Patch(facecolor=color, label=emotion, alpha=0.7)
                   for emotion, color in emotion_colors.items()]
fig.legend(handles=legend_elements, loc='upper right', ncol=4,
           bbox_to_anchor=(0.98, 0.98))

plt.tight_layout()
plt.show()
```