#Cell 01 — Environment, paths, reproducibility

```
# === Cell 01: Environment, paths, reproducibility ===
import os, sys, math, random, shutil, warnings
from pathlib import Path

import numpy as np
import pandas as pd
import torch
import torchvision

warnings.filterwarnings("ignore")

def in_colab() -> bool:
    return "google.colab" in sys.modules

if in_colab():
    try:
        from google.colab import drive
        drive.mount("/content/drive", force_remount=False)
        print("[Env] Google Drive mounted.")
    except Exception as e:
        print(f"[Env][WARN] Drive mount failed: {e}")

# Root dirs (local)
PROJECT_ROOT  = Path("./project"); PROJECT_ROOT.mkdir(parents=True, 
exist_ok=True)
DATA_ROOT     = Path("./data");    DATA_ROOT.mkdir(parents=True, 
exist_ok=True)
CKPT_DIR      = PROJECT_ROOT / "checkpoints"; 
CKPT_DIR.mkdir(parents=True, exist_ok=True)
LOG_DIR       = PROJECT_ROOT / "logs"; 
LOG_DIR.mkdir(parents=True, exist_ok=True)

# Seeds
SEED = 42
random.seed(SEED); np.random.seed(SEED); torch.manual_seed(SEED)
if torch.cuda.is_available(): torch.cuda.manual_seed_all(SEED)

# Optional strict determinism (slower but reproducible)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

# Device
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"[Env] torch={torch.__version__}, 
torchvision={torchvision.__version__}, device={device}")

# Data path (edit if needed)
FER_CSV_PATH = Path("/content/drive/MyDrive/fer2013.csv") if
```

```
in_colab() else Path("./fer2013.csv")
print(f"[Env] CSV path → {FER_CSV_PATH}")
```

```
Drive already mounted at /content/drive; to attempt to forcibly
remount, call drive.mount("/content/drive", force_remount=True).
[Env] Google Drive mounted.
[Env] torch=2.8.0+cu126, torchvision=0.23.0+cu126, device=cuda
[Env] CSV path → /content/drive/MyDrive/fer2013.csv
```

#Cell 02 — Global config (single source of truth)

```
# === Cell 02: Global config (single source of truth) ===
CONFIG = {
    # IO
    "FER_CSV_PATH": FER_CSV_PATH,
    "SAVE_BEST_PATH": CKPT_DIR / "best_fer.pth",
    # Data
    "IMG_SIZE": 96,
    "BATCH_SIZE": 192,          # tune for your GPU
    "NUM_WORKERS": 6,           # 4–8 is fine on Colab
    # Training toggles
    "USE_AUG": True,
    "USE_AUG_ADV": True,        # enables the advanced FER policy
    "AUG_ALPHA": 0.65,          # AugMix-lite blend
    "USE_MIXUP": True,
    "USE_CUTMIX": True,
    "USE_EMA": True,
    "USE_TTA": True,            # only for TEST; validation remains
clean
    # Curriculum / late-phase controls
    "AUG_CAP_LATE": True,       # cap augmentation strength in final
30%
    "TAPER_MIX_LATE": True,     # taper mixing after 50% epochs
    # Compute
    "USE_AMP": torch.cuda.is_available(),
}

HP = {
    "EPOCHS": 50,
    "LR": 3e-4,
    "WD": 1e-4,
    "WARMUP_EPOCHS": 4,
    "LR_MIN": 1e-6,
    "PATIENCE": 8,
    "EMA_DECAY": 0.999,
    "MIXUP_ALPHA": 0.30,
    "CUTMIX_ALPHA": 1.00,
    "AUG_RAMP_EPOCHS": 0.30,   # fraction of total epochs
}
```

```
for k in sorted(CONFIG): print(f"[CFG] {k:16s}: {CONFIG[k]}")
for k in sorted(HP):     print(f"[HP ] {k:16s}: {HP[k]}")
```

```
[CFG] AUG_ALPHA        : 0.65
[CFG] AUG_CAP_LATE     : True
[CFG] BATCH_SIZE       : 192
[CFG] FER_CSV_PATH     : /content/drive/MyDrive/fer2013.csv
[CFG] IMG_SIZE         : 96
[CFG] NUM_WORKERS      : 6
[CFG] SAVE_BEST_PATH   : project/checkpoints/best_fer.pth
[CFG] TAPER_MIX_LATE   : True
[CFG] USE_AMP          : True
[CFG] USE_AUG          : True
[CFG] USE_AUG_ADV      : True
[CFG] USE_CUTMIX       : True
[CFG] USE_EMA          : True
[CFG] USE_MIXUP        : True
[CFG] USE_TTA          : True
[HP ] AUG_RAMP_EPOCHS  : 0.3
[HP ] CUTMIX_ALPHA     : 1.0
[HP ] EMA_DECAY        : 0.999
[HP ] EPOCHS           : 50
[HP ] LR               : 0.0003
[HP ] LR_MIN           : 1e-06
[HP ] MIXUP_ALPHA      : 0.3
[HP ] PATIENCE         : 8
[HP ] WARMUP_EPOCHS    : 4
[HP ] WD               : 0.0001
```

#Cell 03 — Load FER2013 and split

```
# === Cell 03: Load FER2013 and split ===
from pathlib import Path
FER_CSV_PATH = Path(CONFIG["FER_CSV_PATH"])
assert FER_CSV_PATH.exists(), f"CSV not found: {FER_CSV_PATH}"

df = pd.read_csv(FER_CSV_PATH)
assert {"emotion","pixels"}.issubset(set(df.columns)), f"Bad columns:
{df.columns.tolist()}"
print(df["Usage"].value_counts())

train_df = df[df["Usage"]=="Training"].reset_index(drop=True)
val_df   = df[df["Usage"]=="PublicTest"].reset_index(drop=True)
test_df  = df[df["Usage"]=="PrivateTest"].reset_index(drop=True)
print(f"[Split] train={len(train_df)}, val={len(val_df)},
test={len(test_df)}")
```

```
Usage
Training       28709
```

```
PublicTest      3589
PrivateTest     3589
Name: count, dtype: int64
[Split] train=28709, val=3589, test=3589
```

#Cell 04 — Dataset (48→96), returns tensor in [0..255], 1×H×W

```
# === Cell 04: Dataset (48→96), returns [1,H,W] in 0..255 float ===
import torchvision.transforms.functional as VF
from torch.utils.data import Dataset

class FER2013Dataset(Dataset):
    def __init__(self, df: pd.DataFrame, img_size: int = 96):
        self.df = df.reset_index(drop=True)
        self.img_size = int(img_size)
        if len(self.df) > 0:
            _ = self._get_x(0)

    def _get_x(self, i: int) -> torch.Tensor:
        px = self.df.iloc[i]["pixels"]
        arr = np.fromstring(str(px), sep=" ", dtype=np.float32)
        assert arr.size == 48*48, f"Row {i}: expected 2304 pixels, got 
{arr.size}"
        x = torch.from_numpy(arr.reshape(48, 48)).unsqueeze(0)  # 
[1,48,48], float32 in 0..255
        x = VF.resize(
            x,
            [self.img_size, self.img_size],

interpolation=torchvision.transforms.InterpolationMode.BILINEAR,
            antialias=True,
        )
        return x

    def __len__(self): return len(self.df)

    def __getitem__(self, i):
        x = self._get_x(i).contiguous()  # [1,H,W], float32 0..255
        y = int(self.df.iloc[i]["emotion"])
        return x, y

IMG_SIZE = int(CONFIG["IMG_SIZE"])
train_ds = FER2013Dataset(train_df, IMG_SIZE)
val_ds   = FER2013Dataset(val_df,   IMG_SIZE)
test_ds  = FER2013Dataset(test_df,  IMG_SIZE)
print("[Dataset] ready.")

[Dataset] ready.
```

#Cell 05 — DataLoaders

```
# === Cell 05: DataLoaders ===
from torch.utils.data import DataLoader

BATCH = int(CONFIG["BATCH_SIZE"])
NUM_WORKERS = int(CONFIG["NUM_WORKERS"])
PIN = bool(torch.cuda.is_available())  # safer on CPU-only runs

train_dl = DataLoader(
    train_ds, batch_size=BATCH, shuffle=True,
    num_workers=NUM_WORKERS, pin_memory=PIN,
persistent_workers=(NUM_WORKERS>0)
)
val_dl   = DataLoader(
    val_ds,   batch_size=BATCH*2, shuffle=False,
    num_workers=NUM_WORKERS, pin_memory=PIN,
persistent_workers=(NUM_WORKERS>0)
)
test_dl  = DataLoader(
    test_ds,  batch_size=BATCH*2, shuffle=False,
    num_workers=NUM_WORKERS, pin_memory=PIN,
persistent_workers=(NUM_WORKERS>0)
)

xb, yb = next(iter(val_dl))
print(f"[Check] val batch: {xb.shape}, range [{xb.min():.1f},
{xb.max():.1f}]")

[Check] val batch: torch.Size([384, 1, 96, 96]), range [0.0,255.0]
```

#Cell 06 — Advanced augmentation primitives (photometric, geometric, occlusion, elastic)

```
# === Cell 06: Advanced augmentation primitives (grayscale) ===
import io
from PIL import Image, ImageOps
import torch.nn.functional as F

def _to_pil_gray(x255: torch.Tensor) -> Image.Image:
    x = x255.clamp(0,255).to(torch.uint8).squeeze(0).cpu().numpy()
    return Image.fromarray(x, mode='L')

def _from_pil_gray(img: Image.Image) -> torch.Tensor:
    return torch.tensor(np.array(img, dtype=np.uint8),
dtype=torch.float32).unsqueeze(0)

def _clip(x): return x.clamp(0.0, 255.0)

# photometric
def gauss_noise(x, sigma=0.02): return _clip(x +
torch.randn_like(x)*(sigma*255.))
def rand_gamma(x, gmin=0.85, gmax=1.25):
```

```
    g = random.uniform(gmin,gmax); x01=(x/255.).clamp(0,1); return
(x01**g)*255.
def rand_contrast(x, scale=0.25):
    c = 1.0+random.uniform(-scale,scale);
m=x.mean(dim=(1,2),keepdim=True); return _clip((x-m)*c+m)
def rand_equalize(x):
    img=_to_pil_gray(x); img=ImageOps.equalize(img); return
_from_pil_gray(img).to(x.dtype).to(x.device)
def rand_jpeg(x, qmin=55, qmax=85):
    img=_to_pil_gray(x); buf=io.BytesIO();
img.save(buf,format='JPEG',quality=random.randint(qmin,qmax))
    buf.seek(0); img2=Image.open(buf).convert('L'); return
_from_pil_gray(img2).to(x.dtype).to(x.device)
def rand_vignette(x, strength=0.25):
    _,H,W=x.shape; yy,xx=torch.meshgrid(torch.linspace(-
1,1,H,device=x.device),
                                        torch.linspace(-
1,1,W,device=x.device),indexing='ij')
    r=torch.sqrt(xx**2+yy**2); mask=1.0-
strength*(r/r.max()).clamp(0,1)
    return _clip(x*mask.unsqueeze(0))

# Range-safe blur: convert to [0,1] → blur → back to [0,255]
def rand_blur(x, k=3):
    x01 = (x/255.).clamp(0,1)
    y01 = torchvision.transforms.functional.gaussian_blur(x01,
kernel_size=k)
    return (y01 * 255.0).clamp(0,255)

# geometric
def rand_affine_small(x, max_rot=12, max_trans=0.08, max_shear=8.0,
max_scale=0.08):
    H,W=x.shape[-2:]
    angle=random.uniform(-max_rot,max_rot)
    trans=[int(random.uniform(-
max_trans,max_trans)*W),int(random.uniform(-max_trans,max_trans)*H)]
    scale=1.0+random.uniform(-max_scale,max_scale)
    shear=[random.uniform(-max_shear,max_shear),0.0]
    return torchvision.transforms.functional.affine(x, angle=angle,
translate=trans, scale=scale, shear=shear)

def rand_pad_crop(x, pad=3):
    _,H,W=x.shape; xpad=F.pad(x,(pad,pad,pad,pad),mode='reflect');
i=random.randint(0,2*pad); j=random.randint(0,2*pad)
    return xpad[:,i:i+H, j:j+W]

def rand_hflip(x, p=0.5): return
torchvision.transforms.functional.hflip(x) if random.random()<p else x

# elastic
```

```
def rand_elastic(x, alpha=1.0, sigma=4.0):
    _,H,W=x.shape
    def _gkern(k=21,s=sigma):
        ax=torch.arange(k,device=x.device)-(k-1)/2; ker=torch.exp(-
(ax**2)/(2*s*s)); ker/=ker.sum(); return ker
    k=21; gx=_gkern(k).view(1,1,1,k); gy=_gkern(k).view(1,1,k,1)

dx=F.conv2d(F.conv2d(torch.randn(1,1,H,W,device=x.device),gx,padding=(
0,k//2)),gy,padding=(k//2,0)).squeeze()*alpha

dy=F.conv2d(F.conv2d(torch.randn(1,1,H,W,device=x.device),gx,padding=(
0,k//2)),gy,padding=(k//2,0)).squeeze()*alpha
    yy,xx=torch.meshgrid(torch.linspace(-1,1,H,device=x.device),
                         torch.linspace(-
1,1,W,device=x.device),indexing='ij')
    xx=(xx+dx/(W/2)).clamp(-1,1); yy=(yy+dy/(H/2)).clamp(-1,1)
    grid=torch.stack([xx,yy],dim=-1).unsqueeze(0)
    return F.grid_sample(x.unsqueeze(0), grid, mode='bilinear',
padding_mode='border', align_corners=True).squeeze(0)

# occlusio
```

#Cell 07 — AugMix-lite and advanced augmentation builder (returns [-1,1])

```
# === Cell 07: AugMix-lite + advanced augmentation builder (→ [-1,1])
===
def _apply_bank(x, bank, k=2):
    y=x.clone()
    for _ in range(k):
        y = random.choice(bank)(y)
    return y

def augmix_lite(x, banks, alpha=0.65, branches=2, depth=2):
    mix=x.clone()
    for _ in range(branches):
        y=_apply_bank(x, random.choice(banks), k=depth)
        mix=mix+y
    mix = mix / (branches+1.0)
    return (1-alpha)*x + alpha*mix

def build_advanced_fer_augment(strength: float):
    s=float(max(0.0,min(1.0,strength)))
    # probabilities
    p_photo=0.7*(0.5+0.5*s); p_geom=0.6*(0.5+0.5*s);
p_occl=0.40*(0.5+0.5*s)
    p_equal=0.20*s; p_blur=0.15*s
    # magnitudes
    gamma_rng=(0.85-0.15*s, 1.20+0.05*s)
    contrast=0.20+0.10*s
```

```
    jpeg_q=(55-int(10*s), 85)
    vignette=0.15+0.20*s
    elastic_a=0.6+0.8*s
    rot=10+5*s; shear=6+4*s; trans=0.06+0.03*s; scale=0.06+0.04*s

    photometric_bank = [
        lambda z: gauss_noise(z, sigma=0.015+0.02*s),
        lambda z: rand_gamma(z, *gamma_rng),
        lambda z: rand_contrast(z, scale=contrast),
        lambda z: rand_jpeg(z, qmin=jpeg_q[0], qmax=jpeg_q[1]),
        lambda z: rand_vignette(z, strength=vignette),
    ]
    geometric_bank = [
        lambda z: rand_affine_small(z, max_rot=rot, max_trans=trans,
max_shear=shear, max_scale=scale),
        lambda z: rand_pad_crop(z, pad=3),
        lambda z: rand_hflip(z, p=0.5),
        lambda z: rand_elastic(z, alpha=elastic_a, sigma=4.0),
    ]
    occlusion_bank = [
        lambda z: band_occlusion(z, mode='eyes',  frac=0.16+0.06*s),
        lambda z: band_occlusion(z, mode='mouth', frac=0.16+0.06*s),
        lambda z: band_occlusion(z, mode='top',   frac=0.14+0.06*s),
        lambda z: localized_erasing(z, min_frac=0.01, max_frac=0.05),
    ]
    banks=[photometric_bank, geometric_bank, occlusion_bank]

    def _norm_to_m11(x255):
        x01=(x255/255.).clamp(0,1)
        return (x01 - 0.5) * 2.0

    def _augment(x):
        if random.random() < p_geom:  x = rand_pad_crop(x, pad=3)
        if random.random() < p_blur:  x = rand_blur(x, k=3)
        if random.random() < p_photo: x =
random.choice(photometric_bank)(x)
        x = augmix_lite(x, banks=banks,
alpha=CONFIG.get("AUG_ALPHA",0.65), branches=2, depth=2)
        if random.random() < p_geom:  x =
random.choice(geometric_bank)(x)
        if random.random() < p_occl:  x =
random.choice(occlusion_bank)(x)
        if random.random() < p_equal: x = rand_equalize(x)
        return _norm_to_m11(x)

    return _augment

FER_AUG_FACTORY = build_advanced_fer_augment if
CONFIG.get("USE_AUG_ADV", False) else build_advanced_fer_augment
```

#Cell 08 — Metrics, class weights, losses (Label-Smoothing + Focal composite)

```
# === Cell 08: Metrics, class weights, composite loss ===
import torch.nn as nn
import torch.nn.functional as F
from collections import Counter

def accuracy(logits, targets): return (logits.argmax(1) ==
targets).float().mean()

def compute_class_weights(df) -> torch.Tensor:
    counts = Counter(int(e) for e in df["emotion"].tolist())
    total = sum(counts.values())
    w = torch.tensor([total / max(1, counts.get(c,1)) for c in
range(7)], dtype=torch.float32)
    return w / w.mean()

CLASS_WEIGHTS = compute_class_weights(train_df)

class LabelSmoothingCE(nn.Module):
    def __init__(self, eps=0.10, reduction='mean'):
        super().__init__(); self.eps=eps; self.reduction=reduction
    def forward(self, logits, targets):
        n = logits.size(-1); logp = F.log_softmax(logits, dim=-1)
        with torch.no_grad():
            true = torch.zeros_like(logp).fill_(self.eps/(n-1))
            true.scatter_(1, targets.unsqueeze(1), 1.0 - self.eps)
        loss = -(true * logp).sum(dim=1)
        return loss.mean() if self.reduction=='mean' else loss

class FocalLoss(nn.Module):
    def __init__(self, gamma=1.5, reduction='mean'):
        super().__init__(); self.g=gamma; self.reduction=reduction
    def forward(self, logits, targets):
        ce = F.cross_entropy(logits, targets, reduction='none')
        pt = torch.exp(-ce)
        fl = (1-pt).pow(self.g) * ce
        return fl.mean() if self.reduction=='mean' else fl

class SmoothedFocal(nn.Module):
    def __init__(self, eps=0.10, gamma=1.5, alpha=0.70, weight=None):
        super().__init__(); self.a=alpha; self.w=weight
        self.lsce = LabelSmoothingCE(eps); self.focal =
FocalLoss(gamma)
    def forward(self, logits, targets):
        if self.w is not None:
            ce = F.cross_entropy(logits, targets, reduction='none',
weight=self.w.to(logits.device))
            pt = torch.exp(-ce); fl = (1-pt).pow(1.5) * ce
            ls = self.lsce(logits, targets)
```

```
            return self.a*ls + (1-self.a)*fl.mean()
        return self.a*self.lsce(logits, targets) + (1-
self.a)*self.focal(logits, targets)
```

#Cell 09 — MixUp / CutMix and mixed criterion

```
# === Cell 09: MixUp / CutMix and mixed criterion ===
def mixup_data(x, y, alpha=0.2):
    if alpha <= 0.0: return x, y, 1.0, None
    lam = np.random.beta(alpha, alpha)
    idx = torch.randperm(x.size(0), device=x.device)
    return lam*x + (1-lam)*x[idx], (y, y[idx]), lam, idx

def cutmix_data(x, y, alpha=1.0, min_lam=0.3, max_lam=0.7):
    if alpha <= 0.0: return x, y, 1.0, None
    lam = float(np.clip(np.random.beta(alpha, alpha), min_lam,
max_lam))
    B,C,H,W = x.size(); idx = torch.randperm(B, device=x.device)
    cut_w = int(W * math.sqrt(1 - lam)); cut_h = int(H * math.sqrt(1 -
lam))
    cx, cy = np.random.randint(W), np.random.randint(H)
    x1, x2 = np.clip(cx - cut_w//2, 0, W), np.clip(cx + cut_w//2, 0,
W)
    y1, y2 = np.clip(cy - cut_h//2, 0, H), np.clip(cy + cut_h//2, 0,
H)
    x[:, :, y1:y2, x1:x2] = x[idx, :, y1:y2, x1:x2]
    lam = 1 - ((x2-x1)*(y2-y1) / (W*H + 1e-9))
    return x, (y, y[idx]), lam, idx

def mixed_criterion(criterion, logits, targets_mix, lam):
    if isinstance(targets_mix, tuple):
        y_a, y_b = targets_mix
        return lam * criterion(logits, y_a) + (1-lam) *
criterion(logits, y_b)
    return criterion(logits, targets_mix)
```

#Cell 10 — EMA (exponential moving average)

```
# === Cell 10: EMA ===
import torch.nn as nn

class EMA:
    def __init__(self, model: nn.Module, decay: float = 0.999):
        self.decay=float(decay); self.shadow={}; self.backup={}
        for n,p in model.named_parameters():
            if p.requires_grad: self.shadow[n]=p.data.clone()
    def update(self, model):
        for n,p in model.named_parameters():
            if p.requires_grad:
```

```
                self.shadow[n]=(1-self.decay)*p.data + 
self.decay*self.shadow[n]
    def apply_shadow(self, model):
        self.backup={}
        for n,p in model.named_parameters():
            if p.requires_grad:
                self.backup[n]=p.data.clone(); 
p.data=self.shadow[n].clone()
    def restore(self, model):
        for n,p in model.named_parameters():
            if p.requires_grad:
                p.data=self.backup[n].clone()
        self.backup={}
```

#Cell 11 — CBAM and Sobel stem

```
# === Cell 11: CBAM + Sobel stem ===
import torch.nn.functional as F
import torch.nn as nn
import torch

class CBAM(nn.Module):
    def __init__(self, ch, r=8):
        super().__init__()
        self.mlp = nn.Sequential(
            nn.Conv2d(ch, max(1,ch//r), 1, bias=True), 
nn.ReLU(inplace=True),
            nn.Conv2d(max(1,ch//r), ch, 1, bias=True)
        )
        self.spatial = 
nn.Sequential(nn.Conv2d(2,1,kernel_size=7,padding=3,bias=False), 
nn.Sigmoid())
        self.sigmoid = nn.Sigmoid()
    def forward(self, x):
        ca = self.sigmoid(self.mlp(F.adaptive_avg_pool2d(x,1) + 
F.adaptive_max_pool2d(x,1)))
        x = x * ca
        ms = torch.cat([x.mean(1,keepdim=True), x.max(1,keepdim=True)
[0]], dim=1)
        return x * self.spatial(ms)

class SobelLayer(nn.Module):
    def __init__(self):
        super().__init__()
        kx = torch.tensor([[1,0,-1],[2,0,-2],[1,0,-1]], 
dtype=torch.float32)
        ky = torch.tensor([[1,2,1],[0,0,0],[-1,-2,-1]], 
dtype=torch.float32)
        w  = torch.stack([kx, ky]).unsqueeze(1)   # (2,1,3,3)
```

```
        self.register_buffer('w', w)
    def forward(self, x):                               # x: [B,1,H,W]
        edges = F.conv2d(x, self.w, padding=1)      # [B,2,H,W]
        return torch.cat([x, edges], dim=1)         # [B,3,H,W]
```

#Cell 12 — Model: EfficientNet-B0 + CBAM + Sobel

```
# === Cell 12: HybridEffNet (EfficientNet-B0 + CBAM + Sobel) ===
from torchvision.models import efficientnet_b0,
EfficientNet_B0_Weights

CLASSIFIER_DROPOUT = 0.30
USE_CBAM = True

class HybridEffNet(nn.Module):
    def __init__(self, num_classes=7,
classifier_dropout=CLASSIFIER_DROPOUT, use_cbam=USE_CBAM):
        super().__init__()
        self.device = device
        base =
efficientnet_b0(weights=EfficientNet_B0_Weights.DEFAULT)
        self.sobel    = SobelLayer()          # 1→3 ch stem
        self.features = base.features
        self.pool     = nn.AdaptiveAvgPool2d(1)
        self.cbam     = CBAM(1280) if use_cbam else None
        self.bn       = nn.BatchNorm1d(1280)
        self.drop     = nn.Dropout(p=classifier_dropout)
        self.head     = nn.Linear(1280, num_classes)
        self.to(self.device)

    def forward(self, x1):                        # x1 in [-1,1],
[B,1,H,W]
        x3 = self.sobel(x1)                       # [B,3,H,W]
        f  = self.features(x3)                    # [B,1280,h,w]
        if self.cbam is not None:
            f = self.cbam(f)
        f  = self.pool(f).flatten(1)              # [B,1280]
        f  = self.bn(f)
        f  = self.drop(f)
        return self.head(f)
```

#Cell 13 — Optimizer, scheduler, early stopping

```
# === Cell 13: Optimizer, Warmup-Cosine, EarlyStopping ===
def make_adamw(params, lr, wd): return torch.optim.AdamW(params,
lr=lr, weight_decay=wd)

class WarmupCosine:
    def __init__(self, opt, warmup_epochs, max_epochs, lr_min=1e-6,
```

```
lr_max=None):
        self.opt=opt; self.warmup=max(1,int(warmup_epochs));
self.maxe=int(max_epochs); self.t=0
        self.lr_min=lr_min; self.lr_max=lr_max if lr_max is not None
else max(pg['lr'] for pg in opt.param_groups)
    def step(self):
        self.t += 1
        if self.t <= self.warmup:
            lr = self.lr_min + (self.lr_max - self.lr_min) * (self.t /
self.warmup)
        else:
            tt = (self.t - self.warmup) / max(1,(self.maxe -
self.warmup))
            lr = self.lr_min + 0.5*(self.lr_max - self.lr_min)*(1 +
math.cos(math.pi*tt))
        for g in self.opt.param_groups: g['lr'] = lr
        return lr

class EarlyStopping:
    def __init__(self, patience=8, min_delta=1e-4):
        self.patience=int(patience); self.min_delta=float(min_delta);
self.best=float('inf'); self.bad=0
    def step(self, val_loss):
        if val_loss < self.best - self.min_delta: self.best=val_loss;
self.bad=0; return False
        self.bad += 1; return self.bad >= self.patience
```

#Cell 14 — Training loop with advanced aug, MixUp/CutMix, EMA, AMP

```
# === Cell 14: fit_with_aug (advanced aug + MixUp/CutMix + EMA + AMP)
===
def fit_with_aug(model: nn.Module, train_dl, val_dl, hp, cfg):
    device = model.device
    weight = CLASS_WEIGHTS.to(device)
    criterion = SmoothedFocal(eps=0.10, gamma=1.5, alpha=0.70,
weight=weight)

    opt   = make_adamw(model.parameters(), lr=hp["LR"], wd=hp["WD"])
    sched = WarmupCosine(opt, warmup_epochs=hp["WARMUP_EPOCHS"],
max_epochs=hp["EPOCHS"], lr_min=hp["LR_MIN"])
    stopper = EarlyStopping(patience=hp["PATIENCE"])
    ema = EMA(model, decay=hp["EMA_DECAY"]) if cfg["USE_EMA"] else
None
    scaler = torch.cuda.amp.GradScaler(enabled=cfg["USE_AMP"])

    total_epochs = int(hp["EPOCHS"])
    ramp_epochs  = max(1, int(float(hp["AUG_RAMP_EPOCHS"]) *
total_epochs))
    cap_late     = bool(cfg.get("AUG_CAP_LATE", True))
```

```
    taper_late   = bool(cfg.get("TAPER_MIX_LATE", True))

    history = []; best_val = float("inf")

    for epoch in range(1, total_epochs+1):
        model.train()
        s = 0.2 + 0.6 * min(1.0, epoch / ramp_epochs) if
cfg["USE_AUG"] else 0.0
        if cap_late and epoch >= int(0.7*total_epochs): s = min(s,
0.6)
        augment = FER_AUG_FACTORY(s) if cfg["USE_AUG"] else None

        mixup_alpha  = float(hp["MIXUP_ALPHA"])
        cutmix_alpha = float(hp["CUTMIX_ALPHA"])
        use_cutmix   = bool(cfg["USE_CUTMIX"])
        if taper_late and epoch >= int(0.5*total_epochs):
            mixup_alpha  = max(0.1, mixup_alpha * 0.5)
            cutmix_alpha = max(0.5, cutmix_alpha * 0.5)
        if taper_late and epoch >= int(0.7*total_epochs):
            use_cutmix = False

        epoch_loss_sum, seen = 0.0, 0
        for xb, yb in train_dl:
            xb, yb = xb.to(device, non_blocking=True), yb.to(device,
non_blocking=True)
            if augment is not None:
                xb = torch.stack([augment(x) for x in xb])     #
normalized [-1,1]
            else:
                xb = ((xb/255.) - 0.5) * 2.0                   #
deterministic normalization

            opt.zero_grad(set_to_none=True)
            with torch.autocast(device_type="cuda",
dtype=torch.float16, enabled=cfg["USE_AMP"]):
                if cfg["USE_MIXUP"] or use_cutmix:
                    if use_cutmix and random.random() < 0.5:
                        xb, targets_mix, lam, _ = cutmix_data(xb, yb,
alpha=cutmix_alpha, min_lam=0.3, max_lam=0.7)
                    else:
                        xb, targets_mix, lam, _ = mixup_data(xb, yb,
alpha=mixup_alpha)
                    logits = model(xb)
                    loss = mixed_criterion(criterion, logits,
targets_mix, lam)
                else:
                    logits = model(xb)
                    loss = criterion(logits, yb)

            scaler.scale(loss).backward()
```

```
            if torch.cuda.is_available(): scaler.unscale_(opt)
            torch.nn.utils.clip_grad_norm_(model.parameters(), 5.0)
            scaler.step(opt); scaler.update()
            if ema is not None: ema.update(model)

            bs = xb.size(0); epoch_loss_sum += loss.item()*bs; seen +=
bs

        # clean validation
        @torch.no_grad()
        def _eval(loader):
            model.eval(); losses=[]; accs=[]
            for xb, yb in loader:
                xb, yb = xb.to(device), yb.to(device)
                xb = ((xb/255.) - 0.5) * 2.0
                logits = model(xb)
                losses.append(criterion(logits, yb).item())
                accs.append(accuracy(logits, yb).item())
            return float(np.mean(losses)), float(np.mean(accs))

        val_loss, val_acc = _eval(val_dl)
        lr_now = sched.step()
        train_loss = epoch_loss_sum / max(1, seen)
        history.append({"epoch":epoch, "train_loss":train_loss,
"val_loss":val_loss, "val_acc":val_acc, "lr":lr_now})
        print(f"[{epoch:03d}/{total_epochs}] train={train_loss:.4f}
val={val_loss:.4f}  acc={val_acc:.4f}  lr={lr_now:.2e}")

        if val_loss < best_val - 1e-6:
            best_val = val_loss
            torch.save({"model_state": model.state_dict()},
CONFIG["SAVE_BEST_PATH"])
        if stopper.step(val_loss):
            print("[EarlyStopping] stopping."); break

    return history, ema
```

#Cell 15 — Build model and quick probe

```
# === Cell 15: Build model and quick probe ===
model = HybridEffNet(num_classes=7, classifier_dropout=0.30,
use_cbam=True)
model.train()
xb, yb = next(iter(train_dl))
xb = ((xb/255.) - 0.5) * 2.0
with torch.autocast(device_type="cuda", dtype=torch.float16,
enabled=CONFIG["USE_AMP"]):
    logits = model(xb.to(model.device))
    loss = F.cross_entropy(logits, yb.to(model.device))
```

```
loss.backward(); model.zero_grad(set_to_none=True)
print(f"[Probe] logits={tuple(logits.shape)}, loss={loss.item():.4f}")
```

```
[Probe] logits=(192, 7), loss=2.1074
```

Cell 16 — Train (main run)

=== Cell 16: Train main run ===

history, ema_obj = fit_with_aug(model, train_dl, val_dl, HP, CONFIG)

```
# === Cell 16: Train main run ===
history, ema_obj = fit_with_aug(model, train_dl, val_dl, HP, CONFIG)
```

```
[001/50] train=1.4822  val=1.2242  acc=0.4529  lr=7.57e-05
[002/50] train=1.3727  val=1.1776  acc=0.4885  lr=1.50e-04
[003/50] train=1.3465  val=1.1199  acc=0.5103  lr=2.25e-04
[004/50] train=1.2914  val=1.0820  acc=0.5424  lr=3.00e-04
[005/50] train=1.2779  val=1.0364  acc=0.5728  lr=3.00e-04
[006/50] train=1.2559  val=1.0154  acc=0.5748  lr=2.99e-04
[007/50] train=1.2288  val=1.0108  acc=0.5880  lr=2.97e-04
[008/50] train=1.2034  val=0.9832  acc=0.6086  lr=2.94e-04
[009/50] train=1.1775  val=0.9821  acc=0.6179  lr=2.91e-04
[010/50] train=1.1779  val=0.9614  acc=0.6243  lr=2.88e-04
[011/50] train=1.1760  val=0.9402  acc=0.6489  lr=2.83e-04
[012/50] train=1.1587  val=0.9498  acc=0.6355  lr=2.78e-04
[013/50] train=1.1890  val=0.9382  acc=0.6417  lr=2.73e-04
[014/50] train=1.1340  val=0.9177  acc=0.6495  lr=2.66e-04
[015/50] train=1.1504  val=0.9362  acc=0.6454  lr=2.60e-04
[016/50] train=1.1504  val=0.9234  acc=0.6474  lr=2.53e-04
[017/50] train=1.1599  val=0.9150  acc=0.6570  lr=2.45e-04
[018/50] train=1.1386  val=0.9159  acc=0.6618  lr=2.37e-04
[019/50] train=1.1285  val=0.9214  acc=0.6549  lr=2.28e-04
[020/50] train=1.1188  val=0.9088  acc=0.6653  lr=2.19e-04
[021/50] train=1.0903  val=0.8915  acc=0.6687  lr=2.10e-04
[022/50] train=1.1097  val=0.9036  acc=0.6701  lr=2.01e-04
[023/50] train=1.0969  val=0.9056  acc=0.6725  lr=1.91e-04
[024/50] train=1.1141  val=0.8942  acc=0.6772  lr=1.81e-04
[025/50] train=1.1008  val=0.8962  acc=0.6750  lr=1.71e-04
[026/50] train=1.0487  val=0.9002  acc=0.6720  lr=1.61e-04
[027/50] train=1.0594  val=0.8849  acc=0.6815  lr=1.50e-04
[028/50] train=1.0623  val=0.8816  acc=0.6717  lr=1.40e-04
[029/50] train=1.0470  val=0.8843  acc=0.6759  lr=1.30e-04
[030/50] train=1.0381  val=0.8825  acc=0.6752  lr=1.20e-04
[031/50] train=1.0135  val=0.8737  acc=0.6886  lr=1.10e-04
[032/50] train=0.9988  val=0.8732  acc=0.6829  lr=1.00e-04
[033/50] train=0.9991  val=0.8696  acc=0.6873  lr=9.09e-05
[034/50] train=1.0176  val=0.8947  acc=0.6803  lr=8.17e-05
```

```
[035/50] train=0.8204  val=0.8747  acc=0.6937  lr=7.28e-05
[036/50] train=0.7566  val=0.8771  acc=0.6849  lr=6.43e-05
[037/50] train=0.7778  val=0.8772  acc=0.6920  lr=5.62e-05
[038/50] train=0.7570  val=0.8820  acc=0.6906  lr=4.85e-05
[039/50] train=0.7835  val=0.8769  acc=0.6907  lr=4.12e-05
[040/50] train=0.7631  val=0.8812  acc=0.6955  lr=3.45e-05
[041/50] train=0.7469  val=0.8859  acc=0.6945  lr=2.84e-05
[EarlyStopping] stopping.
```

=== Cell 17: Optional late-phase clean fine-tune (short tail) ===

```
# === Cell 17: Optional late-phase clean fine-tune (short tail) ===
from copy import deepcopy

if Path(CONFIG["SAVE_BEST_PATH"]).exists():
    ckpt = torch.load(CONFIG["SAVE_BEST_PATH"], map_location="cpu")
    model.load_state_dict(ckpt["model_state"]);
model.to(model.device).train()

    cfg_tail = dict(CONFIG);  cfg_tail.update({"USE_AUG": False,
"USE_MIXUP": False, "USE_CUTMIX": False})
    HP_TAIL = dict(HP, EPOCHS=8, LR=3e-5, LR_MIN=1e-6,
PATIENCE=max(12, HP["PATIENCE"]))
    criterion_tail = LabelSmoothingCE(eps=0.05)
    opt = make_adamw(model.parameters(), lr=HP_TAIL["LR"],
wd=HP_TAIL["WD"])
    sched = WarmupCosine(opt, warmup_epochs=1,
max_epochs=HP_TAIL["EPOCHS"], lr_min=HP_TAIL["LR_MIN"])
    ema_tail = EMA(model, decay=0.9995)

    for ep in range(1, HP_TAIL["EPOCHS"]+1):
        model.train()
        for xb, yb in train_dl:
            xb, yb = xb.to(model.device), yb.to(model.device)
            xb = ((xb/255.) - 0.5)*2.0
            opt.zero_grad(set_to_none=True)
            with torch.autocast(device_type="cuda",
dtype=torch.float16, enabled=CONFIG["USE_AMP"]):
                loss = criterion_tail(model(xb), yb)
            loss.backward();
torch.nn.utils.clip_grad_norm_(model.parameters(), 5.0)
            opt.step(); ema_tail.update(model)
        sched.step()
        ema_tail.apply_shadow(model)
        with torch.no_grad():
            model.eval()
```

```
            va = []
            for xb, yb in val_dl:
                xb, yb = xb.to(model.device), yb.to(model.device)
                xb = ((xb/255.) - 0.5)*2.0
                va.append(accuracy(model(xb), yb).item())
        ema_tail.restore(model)
        print(f"[Tail {ep:02d}] val_acc={np.mean(va):.4f}")
```

```
[Tail 01] val_acc=0.6865
[Tail 02] val_acc=0.6865
[Tail 03] val_acc=0.6871
[Tail 04] val_acc=0.6863
[Tail 05] val_acc=0.6845
[Tail 06] val_acc=0.6842
[Tail 07] val_acc=0.6835
[Tail 08] val_acc=0.6847
```

=== Cell 18: Evaluation (val clean; test clean + optional TTA) ===

```
# === Cell 20: Optional BatchNorm recalibration (clean, device-safe)
===
from torch.optim.swa_utils import update_bn
import torch, copy
import torch.nn as nn
from torch.utils.data import DataLoader, Dataset

def has_batchnorm(m: nn.Module) -> bool:
    return any(isinstance(x, nn.modules.batchnorm._BatchNorm) for x in
m.modules())

# --- 0) Evaluation transform from the validation loader (if
available) ---
def _get_eval_transform():
    if 'val_dl' in globals() and hasattr(val_dl, 'dataset') and
hasattr(val_dl.dataset, 'transform'):
        return val_dl.dataset.transform
    return None

EVAL_TF = _get_eval_transform()

# --- 1) Build a CLEAN train loader that uses the eval transform (no
aug) ---
class _TransformView(Dataset):
    """Wrap an existing Dataset and override its transform for
__getitem__."""
    def __init__(self, base_ds, transform):
```

```
        self.base = base_ds
        self.transform = transform
    def __len__(self):  return len(self.base)
    def __getitem__(self, i):
        x, y = self.base[i]
        if self.transform is not None:
            x = self.transform(x)
        return x, y

if EVAL_TF is not None:
    train_ds_clean = _TransformView(train_dl.dataset, EVAL_TF)
    train_dl_clean = DataLoader(
        train_ds_clean,
        batch_size=val_dl.batch_size,   # match val/test batch size
        shuffle=False,
        num_workers=val_dl.num_workers,
        pin_memory=True,
        persistent_workers=True
    )
else:
    print("[BN][WARN] No eval transform detected; reusing train_dl
with explicit normalization.")
    train_dl_clean = train_dl

# --- 2) BN recalibration ---
if has_batchnorm(model):
    print("[BN] Recalibrating BN running stats...")
    dev = next(model.parameters()).device
    was_training = model.training
    model.train()

    # If evaluating EMA weights, apply them BEFORE recalibration.
    # try: ema_tail.apply_shadow(model)
    # except NameError: pass

    @torch.no_grad()
    def _clean_iter(dloader):
        for xb, _ in dloader:
            xb = xb.to(dev, non_blocking=True)
            if EVAL_TF is None:                 # only if we didn't
inherit Normalize
                xb = ((xb / 255.) - 0.5) * 2.0   # [-1, 1]
            yield xb                             # update_bn expects
the input tensor

    update_bn(_clean_iter(train_dl_clean), model)
    model.train(was_training); model.eval()
    print("[BN] Done.")

    # --- 3) Quick clean evaluation (consistent with above
```

```
normalization) ---
    @torch.no_grad()
    def _eval_quick(loader):
        model.eval()
        correct = total = 0
        dev = next(model.parameters()).device
        for xb, yb in loader:
            xb, yb = xb.to(dev, non_blocking=True), yb.to(dev,
non_blocking=True)
            if EVAL_TF is None:
                xb = ((xb / 255.) - 0.5) * 2.0
            pred = model(xb).argmax(1)
            correct += (pred == yb).sum().item()
            total   += yb.size(0)
        return correct / max(1, total)

    print(f"[BN] val_post={_eval_quick(val_dl):.4f}
test_post={_eval_quick(test_dl):.4f}")

    # If you temporarily applied EMA above and want to revert:
    # try: ema_tail.restore(model)
    # except NameError: pass
else:
    print("[BN] No BN layers found; skipping.")
```

```
[BN][WARN] No eval transform detected; reusing train_dl with explicit
normalization.
[BN] Recalibrating BN running stats...
[BN] Done.
[BN] val_post=0.6835  test_post=0.7041
```

```
# === Cell 18: Evaluation (val clean; test clean + optional TTA) ===
@torch.no_grad()
def eval_loader(model, loader):
    model.eval(); total=0; correct=0
    for xb, yb in loader:
        xb, yb = xb.to(model.device), yb.to(model.device)
        xb = ((xb/255.) - 0.5) * 2.0
        pred = model(xb).argmax(1)
        correct += (pred==yb).sum().item(); total += yb.size(0)
    return correct/total

@torch.no_grad()
def eval_loader_tta(model, loader, n=6):
    """
    TTA with H-flip variants. We average PROBABILITIES (softmax), not
logits.
    """
    model.eval(); total=0; correct=0
    for xb, yb in loader:
```

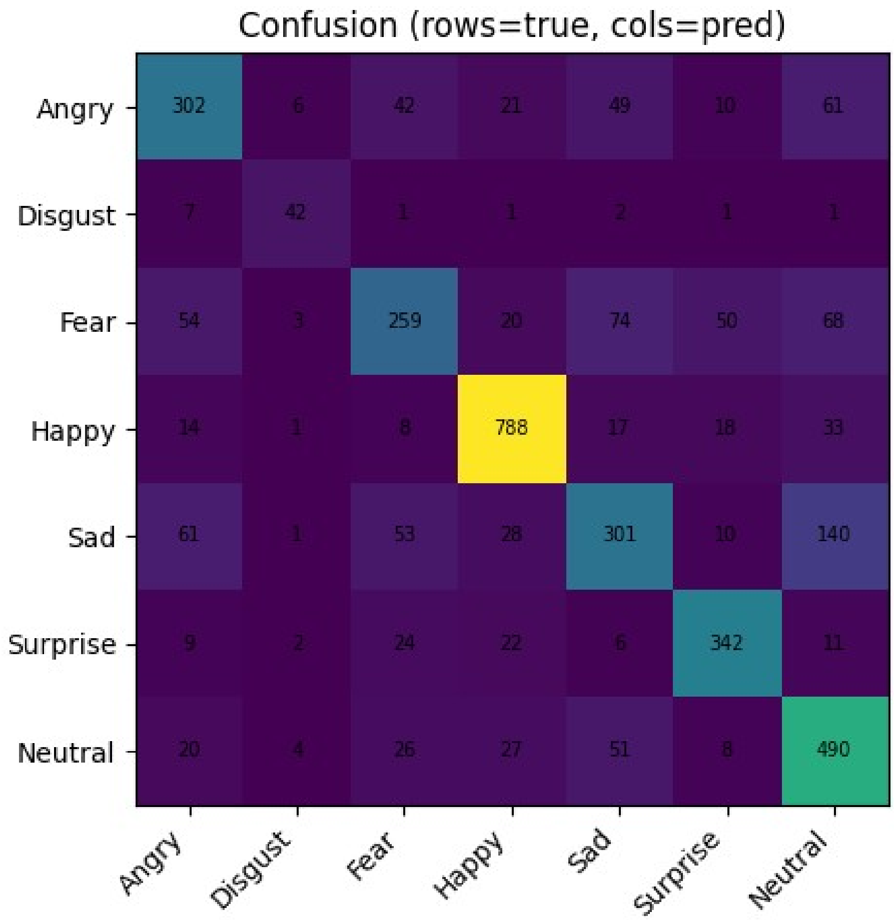
```
        xb, yb = xb.to(model.device), yb.to(model.device)
        xb = ((xb/255.) - 0.5) * 2.0
        prob_sum = None
        for t in range(n):
            # simple TTA: alternate original and horizontal flip
            xb_t = xb.flip(-1) if (t % 2 == 1) else xb
            logits = model(xb_t)
            probs  = torch.softmax(logits, dim=1)
            prob_sum = probs if prob_sum is None else (prob_sum +
probs)
        pred = (prob_sum / float(n)).argmax(1)
        correct += (pred==yb).sum().item(); total += yb.size(0)
    return correct/total

val_acc_base  = eval_loader(model, val_dl)
test_acc_base = eval_loader(model, test_dl)

val_acc_ema = test_acc_ema = None
if 'ema_obj' in globals() and ema_obj is not None:
    ema_obj.apply_shadow(model)
    val_acc_ema  = eval_loader(model, val_dl)
    test_acc_ema = eval_loader(model, test_dl)
    ema_obj.restore(model)

test_acc_tta = None
if CONFIG["USE_TTA"]:
    if 'ema_obj' in globals() and ema_obj is not None:
        ema_obj.apply_shadow(model)
        test_acc_tta = eval_loader_tta(model, test_dl, n=6)
        ema_obj.restore(model)
    else:
        test_acc_tta = eval_loader_tta(model, test_dl, n=6)

print(f"[Eval] val_base={val_acc_base:.4f}  val_ema={val_acc_ema}")
print(f"[Eval] test_base={test_acc_base:.4f} test_ema={test_acc_ema}
test_tta={test_acc_tta}")
```

```
[Eval] val_base=0.6835  val_ema=0.685427695736974
[Eval] test_base=0.7041 test_ema=0.7032599609919198
test_tta=0.7040958484257454
```

=== Cell 19: Confusion matrix + per-class accuracy (test) ===

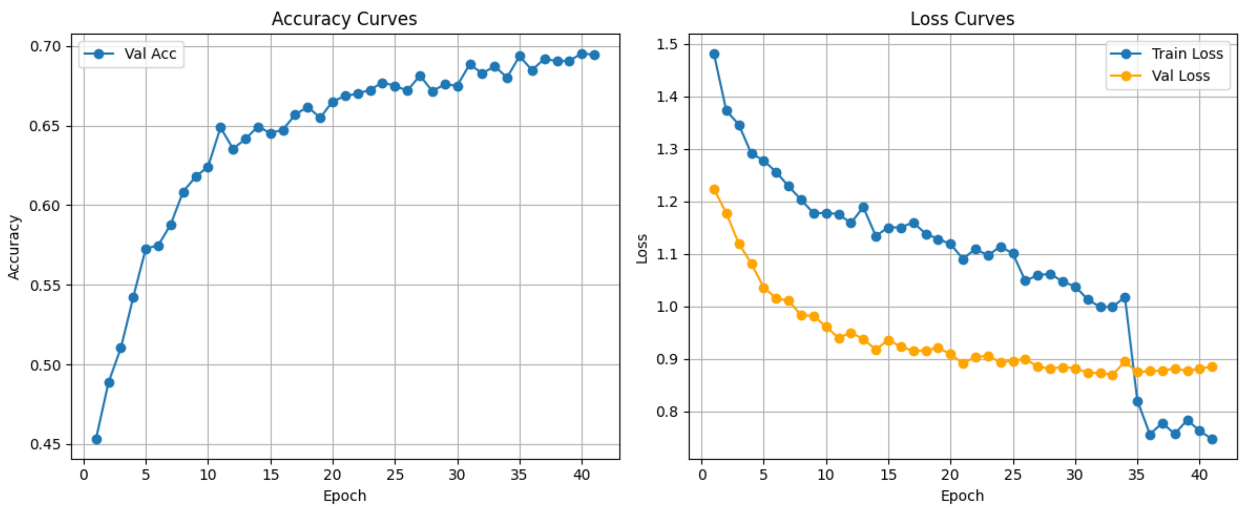
```
# === Cell 19: Confusion matrix + per-class accuracy (test) ===
import itertools
IDX2EMO =
```

```
{0:'Angry',1:'Disgust',2:'Fear',3:'Happy',4:'Sad',5:'Surprise',6:'Neut
ral'}

@torch.no_grad()
def confusion_matrix_and_report(model, loader, num_classes=7,
use_ema=True):
    ema_local = globals().get("ema_obj", None)
    if use_ema and ema_local is not None:
ema_local.apply_shadow(model)
    model.eval();
cm=torch.zeros(num_classes,num_classes,dtype=torch.int64)
    for xb, yb in loader:
        xb, yb = xb.to(model.device), yb.to(model.device)
        xb = ((xb/255.) - 0.5) * 2.0
        preds = model(xb).argmax(1)
        for t,p in zip(yb.view(-1), preds.view(-1)):
            cm[t.long(), p.long()] += 1
    if use_ema and ema_local is not None: ema_local.restore(model)
    denom = cm.sum(1).clamp(min=1).cpu().numpy()
    per_class = (cm.diag().cpu().numpy() / denom) * 100.0
    import matplotlib.pyplot as plt
    plt.figure(figsize=(6,5)); plt.imshow(cm.cpu());
plt.title("Confusion (rows=true, cols=pred)")
    plt.xticks(range(7), [IDX2EMO[i] for i in range(7)], rotation=45,
ha='right')
    plt.yticks(range(7), [IDX2EMO[i] for i in range(7)])
    for i,j in itertools.product(range(7), range(7)):
        if cm[i,j]>0:
plt.text(j,i,int(cm[i,j]),ha='center',va='center',fontsize=7)
    plt.tight_layout(); plt.show()
    for i,a in enumerate(per_class):
        print(f"{IDX2EMO[i]:>8s}: {a:.2f}%")

confusion_matrix_and_report(model, test_dl, use_ema=True)
```




```
   Angry: 61.51%
 Disgust: 76.36%
    Fear: 49.05%
   Happy: 89.65%
     Sad: 50.67%
Surprise: 82.21%
 Neutral: 78.27%

# === Cell: Plot Accuracy and Loss Curves ===
import matplotlib.pyplot as plt

# Example structure of history:
# history = [
#   {'epoch': 1, 'train_loss': 1.45, 'val_loss': 1.22, 'train_acc':
0.46, 'val_acc': 0.48, 'test_acc': 0.47},
#   {'epoch': 2, 'train_loss': 1.38, 'val_loss': 1.18, 'train_acc':
0.51, 'val_acc': 0.53, 'test_acc': 0.52},
#   ...
# ]

epochs     = [m['epoch']      for m in history]
```

```python
train_loss = [m.get('train_loss') for m in history]
val_loss   = [m.get('val_loss')   for m in history]
train_acc  = [m.get('train_acc')  for m in history]
val_acc    = [m.get('val_acc')    for m in history]

# If you logged test_acc per epoch
test_acc   = [m.get('test_acc') for m in history] if 'test_acc' in
history[0] else None

plt.figure(figsize=(12,5))

# 1. Accuracy plot
plt.subplot(1,2,1)
if train_acc[0] is not None:
    plt.plot(epochs, train_acc, label="Train Acc", marker='o')
plt.plot(epochs, val_acc, label="Val Acc", marker='o')
if test_acc is not None and any(v is not None for v in test_acc):
    plt.plot(epochs, test_acc, label="Test Acc", marker='x')
elif 'test_post' in globals():
    plt.axhline(test_post, color='red', linestyle='--', label=f"Final
Test Acc = {test_post:.4f}")
plt.title("Accuracy Curves")
plt.xlabel("Epoch"); plt.ylabel("Accuracy")
plt.legend(); plt.grid(True)

# 2. Loss plot
plt.subplot(1,2,2)
if train_loss[0] is not None:
    plt.plot(epochs, train_loss, label="Train Loss", marker='o')
plt.plot(epochs, val_loss, label="Val Loss", marker='o',
color='orange')
plt.title("Loss Curves")
plt.xlabel("Epoch"); plt.ylabel("Loss")
plt.legend(); plt.grid(True)

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



=== Cell 21: FLOPs (fvcore) + Accuracy/GFLOP ===

```
%pip install fvcore

Collecting fvcore
  Downloading fvcore-0.1.5.post20221221.tar.gz (50 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 50.2/50.2 kB 4.0 MB/s eta
0:00:00
etadata (setup.py) ... ent already satisfied: numpy in
/usr/local/lib/python3.12/dist-packages (from fvcore) (2.0.2)
Collecting yacs>=0.1.6 (from fvcore)
  Downloading yacs-0.1.8-py3-none-any.whl.metadata (639 bytes)
Requirement already satisfied: pyyaml>=5.1 in
/usr/local/lib/python3.12/dist-packages (from fvcore) (6.0.2)
Requirement already satisfied: tqdm in /usr/local/lib/python3.12/dist-
packages (from fvcore) (4.67.1)
Requirement already satisfied: termcolor>=1.1 in
/usr/local/lib/python3.12/dist-packages (from fvcore) (3.1.0)
Requirement already satisfied: Pillow in
/usr/local/lib/python3.12/dist-packages (from fvcore) (11.3.0)
Requirement already satisfied: tabulate in
/usr/local/lib/python3.12/dist-packages (from fvcore) (0.9.0)
Collecting iopath>=0.1.7 (from fvcore)
  Downloading iopath-0.1.10.tar.gz (42 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 42.2/42.2 kB 3.6 MB/s eta
0:00:00
etadata (setup.py) ... ent already satisfied: typing_extensions in
/usr/local/lib/python3.12/dist-packages (from iopath>=0.1.7->fvcore)
(4.14.1)
Collecting portalocker (from iopath>=0.1.7->fvcore)
```

```
  Downloading portalocker-3.2.0-py3-none-any.whl.metadata (8.7 kB)
Downloading yacs-0.1.8-py3-none-any.whl (14 kB)
Downloading portalocker-3.2.0-py3-none-any.whl (22 kB)
Building wheels for collected packages: fvcore, iopath
  Building wheel for fvcore (setup.py) ... e=fvcore-
0.1.5.post20221221-py3-none-any.whl size=61397
sha256=55e7b721d86f7ef9b255ec252ea20bc70b47f5c8b90d8ac85c494b377d5bf2c
d
  Stored in directory:
/root/.cache/pip/wheels/ed/9f/a5/e4f5b27454ccd4596bd8b62432c7d6b1ca9fa
22aef9d70a16a
  Building wheel for iopath (setup.py) ... e=iopath-0.1.10-py3-none-
any.whl size=31527
sha256=659994305df3b06ec5982643c1d945ae595e75130ba2191dc533308522ad872
a
  Stored in directory:
/root/.cache/pip/wheels/7c/96/04/4f5f31ff812f684f69f40cb1634357812220a
ac58d4698048c
Successfully built fvcore iopath
Installing collected packages: yacs, portalocker, iopath, fvcore
Successfully installed fvcore-0.1.5.post20221221 iopath-0.1.10
portalocker-3.2.0 yacs-0.1.8
```

```
# === Cell 21: FLOPs (fvcore) + Accuracy/GFLOP ===
import importlib, subprocess
try:
    from fvcore.nn import FlopCountAnalysis
except Exception:
    subprocess.check_call([sys.executable, "-m", "pip", "install", "-
q", "fvcore"])
    from fvcore.nn import FlopCountAnalysis

model.eval()
# FLOPs don't depend on value scale; this shape matches the model's 1-
channel input.
dummy = torch.randn(1, 1, CONFIG["IMG_SIZE"], CONFIG["IMG_SIZE"],
device=model.device)
total_flops = FlopCountAnalysis(model, (dummy,)).total()
MFLOPs = total_flops / 1e6
GFLOPs = total_flops / 1e9
print(f"[FLOPs] {GFLOPs:.4f} GFLOPs per forward")

def best_acc(*vals):
    vals=[v for v in vals if isinstance(v,(float,int))]
    return max(vals) if vals else None

acc_best_val  = best_acc(val_acc_base, val_acc_ema)
acc_best_test = best_acc(test_acc_base, test_acc_ema, test_acc_tta)

def efficiency_pct_per_gflop(acc_frac, gflops): return
```

```
(acc_frac*100.0)/gflops

if acc_best_test is not None and GFLOPs>0:
    print(f"[Efficiency] Test Accuracy/GFLOP:
{efficiency_pct_per_gflop(acc_best_test, GFLOPs):.2f} (% per GFLOP)")
```

```
WARNING:fvcore.nn.jit_analysis:Unsupported operator aten::silu_
encountered 49 time(s)
WARNING:fvcore.nn.jit_analysis:Unsupported operator aten::sigmoid
encountered 18 time(s)
WARNING:fvcore.nn.jit_analysis:Unsupported operator aten::mul
encountered 18 time(s)
WARNING:fvcore.nn.jit_analysis:Unsupported operator aten::add_
encountered 9 time(s)
WARNING:fvcore.nn.jit_analysis:Unsupported operator
aten::adaptive_max_pool2d encountered 1 time(s)
WARNING:fvcore.nn.jit_analysis:Unsupported operator aten::add
encountered 1 time(s)
WARNING:fvcore.nn.jit_analysis:Unsupported operator aten::mean
encountered 1 time(s)
WARNING:fvcore.nn.jit_analysis:The following submodules of the model
were never called during the trace of the graph. They may be unused,
or they were accessed by direct calls to .forward() or via other
python methods. In the latter case they will have zeros for
statistics, though their statistics will still contribute to their
parent calling module.
features.1.0.stochastic_depth, features.2.0.stochastic_depth,
features.2.1.stochastic_depth, features.3.0.stochastic_depth,
features.3.1.stochastic_depth, features.4.0.stochastic_depth,
features.4.1.stochastic_depth, features.4.2.stochastic_depth,
features.5.0.stochastic_depth, features.5.1.stochastic_depth,
features.5.2.stochastic_depth, features.6.0.stochastic_depth,
features.6.1.stochastic_depth, features.6.2.stochastic_depth,
features.6.3.stochastic_depth, features.7.0.stochastic_depth

[FLOPs] 0.0747 GFLOPs per forward
[Efficiency] Test Accuracy/GFLOP: 943.19 (% per GFLOP)
```

```
# =========================
# TESTING: accuracy + image predictions
# =========================
import torch, numpy as np
from PIL import Image
import torchvision.transforms.functional as VF

# --- Class names for readability ---
CLASS_NAMES =
['Angry','Disgust','Fear','Happy','Sad','Surprise','Neutral']

# --- Normalisation used for eval ---
```

```
def _to_m11(x: torch.Tensor) -> torch.Tensor:
    # x in [0,255] (uint8/float) -> float in [-1,1]
    return ((x.float() / 255.0) - 0.5) * 2.0

# --- 1) Load the trained checkpoint ---
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

ckpt_path = str(CONFIG.get("SAVE_BEST_PATH", ""))  # e.g.,
"project/checkpoints/best_fer.pth"
assert ckpt_path, "CONFIG['SAVE_BEST_PATH'] is empty; set the
checkpoint path first."

# Rebuild model skeleton exactly as trained
model = HybridEffNet(num_classes=7, classifier_dropout=0.30,
use_cbam=True).to(device)
ckpt = torch.load(ckpt_path, map_location=device)
model.load_state_dict(ckpt["model_state"], strict=True)
model.eval()

# --- 2) Compute and print test accuracy (PrivateTest) ---
@torch.no_grad()
def eval_accuracy(model, loader) -> float:
    model.eval()
    correct, total = 0, 0
    for xb, yb in loader:
        xb = _to_m11(xb.to(device, non_blocking=True))
        yb = yb.to(device, non_blocking=True)
        logits = model(xb)
        pred = logits.argmax(1)
        correct += (pred == yb).sum().item()
        total   += yb.numel()
    return correct / max(1, total)

test_acc = eval_accuracy(model, test_dl)
print(f"[Test] accuracy (PrivateTest) = {test_acc:.4f}")

# --- 3a) Predict a few samples from the FER2013 test loader ---
@torch.no_grad()
def preview_test_predictions(model, loader, n=12):
    model.eval()
    xb, yb = next(iter(loader))                  # one batch
    xb = xb[:n]                                  # first n images
    gt = yb[:n].cpu().numpy()
    xb_dev = _to_m11(xb.to(device, non_blocking=True))
    logits = model(xb_dev)
    probs  = logits.softmax(1).cpu().numpy()
    pred   = probs.argmax(1)
    # print a small table
    print("\n[Index]  Pred (pmax)     |  GT")
    for i in range(n):
```

```python
        pclass = int(pred[i]); gclass = int(gt[i])
        pmax   = float(probs[i, pclass])
        print(f"{i:>6d}  {CLASS_NAMES[pclass]:<12s} ({pmax:0.3f}) | {CLASS_NAMES[gclass]}")
    return pred, gt

_ = preview_test_predictions(model, test_dl, n=12)

# --- 3b) Predict arbitrary external images (file paths) ---
@torch.no_grad()
def predict_images(model, image_paths):
    """
    image_paths: List[str] to arbitrary images.
    Preprocessing: grayscale -> resize to 96x96 -> tensor [1,H,W] -> [-1,1].
    """
    model.eval()
    batch = []
    for path in image_paths:
        img = Image.open(path).convert("L")            # force grayscale
        img = img.resize((CONFIG["IMG_SIZE"], CONFIG["IMG_SIZE"]), Image.BILINEAR)
        x = torch.from_numpy(np.array(img, dtype=np.uint8))[None, ...]  # [1,H,W] uint8
        batch.append(x)
    xb = torch.stack(batch, dim=0)                     # [B,1,H,W]
    xb = _to_m11(xb).to(device, non_blocking=True)
    logits = model(xb)
    probs  = logits.softmax(1).cpu().numpy()
    preds  = probs.argmax(1)
    # pretty-print
    print("\n[External Image Predictions]")
    for path, p in zip(image_paths, preds):
        print(f"{path}  ->  {CLASS_NAMES[int(p)]} (p={probs[list(preds).index(p), int(p)]:.3f})")
    return preds, probs

# Example usage for external files (uncomment and set your paths):
# preds, probs = predict_images(model, [
#     "/content/some_face1.png",
#     "/content/some_face2.jpg",
# ])
```

```
[Test] accuracy (PrivateTest) = 0.6982

[Index]  Pred (pmax)     |  GT
     0  Fear         (0.390) |  Angry
     1  Sad          (0.557) |  Surprise
     2  Fear         (0.681) |  Neutral
```

```
     3  Sad          (0.366) |  Sad
     4  Fear         (0.262) |  Fear
     5  Angry        (0.801) |  Angry
     6  Sad          (0.399) |  Sad
     7  Happy        (0.688) |  Happy
     8  Fear         (0.479) |  Angry
     9  Happy        (0.767) |  Happy
    10  Happy        (0.581) |  Surprise
    11  Happy        (0.685) |  Happy

# === Cell B: Visualize predictions on Test images (robust / auto-
range) ===
import torch, numpy as np, matplotlib.pyplot as plt
from torch.utils.data import DataLoader

# Class names (adjust if your label order differs)
Labels = ['Angry','Disgust','Fear','Happy','Sad','Surprise','Neutral']

# If you used my BN-recal cell, EVAL_TF may exist. Otherwise this
stays None.
EVAL_TF = globals().get('EVAL_TF', None)

def _transform_includes_normalize(transform) -> bool:
    """Detects torchvision.transforms.Normalize inside a Compose-like
transform."""
    try:
        from torchvision.transforms import Normalize
        seq = getattr(transform, 'transforms', None)
        return any(isinstance(t, Normalize) for t in (seq or []))
    except Exception:
        return False

@torch.no_grad()
def _model_ready_batch(xb: torch.Tensor, dev: torch.device) ->
torch.Tensor:
    """
    Returns a tensor ready for the model:
    - If val/test transform already contains Normalize(0.5,0.5), pass
through.
    - Otherwise apply explicit ((x/255)-0.5)*2 normalization.
    """
    xb = xb.to(dev, non_blocking=True)
    need_explicit_norm = True
    if EVAL_TF is not None and _transform_includes_normalize(EVAL_TF):
        need_explicit_norm = False
    if need_explicit_norm:
        xb = ((xb / 255.0) - 0.5) * 2.0
    return xb

def _to_display(img: torch.Tensor) -> np.ndarray:
```

```python
    """
    Convert a single image tensor to HxW in [0,1] for imshow.
    Works for uint8 [0,255], float [0,1], or float [-1,1].
    """
    x = img.detach().cpu()
    if x.ndim == 3 and x.size(0) == 1:  # [1,H,W] -> [H,W]
        x = x[0]
    x = x.float()
    m, M = float(x.min()), float(x.max())
    if M > 1.5:           # likely uint8 [0,255]
        x = x / 255.0
    elif m < -0.25:       # likely [-1,1]
        x = (x * 0.5) + 0.5
    x = x.clamp(0, 1)
    return x.numpy()

@torch.no_grad()
def fetch_batch_and_predict(model, loader: DataLoader):
    """Fetch first batch from loader, run model, return (xb_raw, yb, pred, conf)."""
    model.eval()
    dev = next(model.parameters()).device
    xb, yb = next(iter(loader))
    xb_for_model = _model_ready_batch(xb.clone(), dev)
    logits = model(xb_for_model)
    probs = torch.softmax(logits, dim=1)
    pred  = probs.argmax(1)
    conf  = probs.max(1).values
    return xb, yb, pred.cpu(), conf.cpu()

# If you want EMA weights evaluated, uncomment:
# try: ema_tail.apply_shadow(model)
# except NameError: pass

xb, yb, pred, conf = fetch_batch_and_predict(model, test_dl)

# --- Grid render ---
K = min(25, xb.size(0))   # number of images to show
cols = 5
rows = int(np.ceil(K / cols))
plt.figure(figsize=(cols * 3, rows * 3))

for i in range(K):
    ax = plt.subplot(rows, cols, i + 1)
    ax.imshow(_to_display(xb[i]), cmap='gray', interpolation='nearest')
    t = Labels[int(yb[i])]
    p = Labels[int(pred[i])]
    c = float(conf[i])
    ax.set_title(f"P:{p} ({c:.2f})\nT:{t}", fontsize=9)
```

```python
    ax.axis('off')

plt.tight_layout()
plt.show()

# If you applied EMA above and want to revert to base weights,
uncomment:
# try: ema_tail.restore(model)
# except NameError: pass
```

=== Cell 22: Save final checkpoint & reload sanity ===

```python
# === Cell 22: Save final checkpoint & reload sanity ===
FINAL_PATH = CKPT_DIR / "final_fer_model.pth"
torch.save({"model_state": model.state_dict()}, FINAL_PATH)
print(f"[Save] {FINAL_PATH}")

ckpt = torch.load(FINAL_PATH, map_location="cpu")
model.load_state_dict(ckpt["model_state"]);
model.to(model.device).eval()
with torch.no_grad():
    xb, yb = next(iter(val_dl))
    xb = ((xb/255.) - 0.5) * 2.0
    out = model(xb.to(model.device))
print("[Reload] Sanity forward OK:", tuple(out.shape))
```

```
[Save] project/checkpoints/final_fer_model.pth
[Reload] Sanity forward OK: (384, 7)
```