Arifa Kokab

AAI-540

Final Project

Facial Expression Analysis Model

Imports and Setup

```
!pip install torchmetrics
```

Show hidden output

```
import torch
from torch.utils.data import Dataset, DataLoader, WeightedRandomSampler
from collections import Counter
from PIL import Image
import timm, torch.nn as nn, torch.optim as optim
from torch.cuda.amp import GradScaler, autocast
from torchmetrics.classification import MulticlassAccuracy
from tqdm.auto import tqdm
import glob, random, itertools
from google.colab import drive
import os, torch
import math
from itertools import islice
from tqdm.auto import tqdm
import torch, numpy as np, pandas as pd, matplotlib.pyplot as plt, seaborn as sns
from sklearn.metrics import classification_report, confusion_matrix
from torch.cuda.amp import autocast
from google.colab import files
import os, pathlib
from torchvision import transforms
```

```
# Mount Google Drive
from google.colab import drive
drive.mount('/content/drive')
```

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

```
uploaded = files.upload()
token_path = pathlib.Path.home()/".kaggle"
token_path.mkdir(exist_ok=True)
fname = next(iter(uploaded))
(token_path/"kaggle.json").write_bytes(uploaded[fname])
os.chmod(token_path/"kaggle.json", 0o600)
!pip install -q kaggle
```

Choose Files kaggle (3).json

- **kaggle (3).json**(application/json) - 69 bytes, last modified: 6/16/2025 - 100% done

Saving kaggle (3).json to kaggle (3) (1).json

Download and Extract Datasets (FERPlus & RAF-DB)

```
# Download the new FERPlus zip
!echo "🔽 Downloading FERPlus from Kaggle (subhaditya/fer2013plus)…"
!kaggle datasets download -d subhaditya/fer2013plus -p /content --force

# Unzip with file-by-file output
!echo "📂 Unzipping FERPlus…"
!unzip -o /content/fer2013plus.zip -d /content/fer2013

# Cleanup ZIP
!rm /content/fer2013plus.zip

# Point loader at the local SSD
FERPLUS_DIR = "/content/fer2013/fer2013"
!echo "✅ FERPlus extracted to $FERPLUS_DIR"
```

Show hidden output

```
# Download RAF-DB from Kaggle
!echo "🔽 Downloading RAF-DB (shuvoalok/raf-db-dataset)…"
!kaggle datasets download -d shuvoalok/raf-db-dataset -p /content --force

# Unzip with file-by-file output
!echo "📂 Unzipping RAF-DB…"
!unzip -o /content/raf-db-dataset.zip -d /content

# Move the extracted DATASET folder into a clean local path
!echo "🚚 Moving to /content/raf_local…"
!rm -rf /content/raf_local
!mv /content/DATASET /content/raf_local

# Cleanup the ZIP to save space
!rm /content/raf-db-dataset.zip

# Confirm
!echo "✅ RAF-DB ready at /content/raf_local"
```

Show hidden output

Dataset Preparation: File Listing and Label Mapping

```
# RAF-DB (from Kaggle)
RAF_ROOT   = "/content/raf_local"
LABEL_MAP  = {
    "1":"surprise","2":"fear","3":"disgust",
    "4":"happy",   "5":"sad", "6":"anger",   "7":"neutral"
}
RAF_TRAIN, RAF_VAL = [], []
for lab_id, emo in LABEL_MAP.items():
    # training split (90%)
    for path in glob.glob(f"{RAF_ROOT}/train/{lab_id}/*.jpg"):
        if hash(path) % 10 == 0:
            RAF_VAL.append((path, emo))
        else:
            RAF_TRAIN.append((path, emo))
    # official test split → include in validation
    for path in glob.glob(f"{RAF_ROOT}/test/{lab_id}/*.jpg"):
        RAF_VAL.append((path, emo))

random.shuffle(RAF_TRAIN)
random.shuffle(RAF_VAL)
```

```
# Summary
print(f"RAF-DB train:   {len(RAF_TRAIN)}  |  RAF-DB val: {len(RAF_VAL)}")
```

```
RAF-DB train:   11043  |  RAF-DB val: 4296
```

```
# Auto-locate the FERPlus “train” folder
train_dirs = [
    d for d in glob.glob('/content/fer2013/**/train', recursive=True)
    if os.path.isdir(d)
]
if not train_dirs:
    raise RuntimeError(f"No FERPlus train/ folder found under /content/fer2013. Checked {train_dirs!r}")
# pick the deepest one (most nested)
fer_train_dir = sorted(train_dirs, key=lambda p: p.count(os.sep), reverse=True)[0]
FERPLUS_DIR   = os.path.dirname(fer_train_dir)   # parent of 'train'
print("✅ FERPlus directory detected as:", FERPLUS_DIR)

# Map raw folders → unified labels
FER_MAP = {
    "anger":     "anger",
    "disgust":   "disgust",
    "fear":      "fear",
    "happiness": "happy",
    "neutral":   "neutral",
    "sadness":   "sad",
    "surprise":  "surprise"
}

# Build the file list & shuffle, using .png files
FER_FILES = []
for raw_cls, uni_cls in FER_MAP.items():
    folder = os.path.join(FERPLUS_DIR, 'train', raw_cls)
    paths  = glob.glob(f"{folder}/*.png")
    if not paths:
        raise RuntimeError(f"No .png images found in {folder}")
    FER_FILES += [(p, uni_cls) for p in paths]

random.shuffle(FER_FILES)

# Sanity print counts
fer_counts = {cls: sum(1 for _,lbl in FER_FILES if lbl==cls) for cls in set(FER_MAP.values())}
print("FERPlus class counts:", fer_counts, "→ total:", len(FER_FILES))
```

```
✅ FERPlus directory detected as: /content/fer2013/fer2013plus/fer2013
FERPlus class counts: {'disgust': 191, 'neutral': 10308, 'surprise': 3562, 'sad': 3514, 'anger': 2466, 'fear': 652, 'happy': 7528} → total: 28221
```

```
# Auto-locate RAF-DB train & test folders

RAF_ROOT = "/content/raf_local"
if not os.path.isdir(RAF_ROOT):
    raise RuntimeError(f"RAF_ROOT not found at {RAF_ROOT}")

# Define the label-ID → emotion map
LABEL_MAP = {
    "1":"surprise","2":"fear","3":"disgust",
    "4":"happy",   "5":"sad","6":"anger","7":"neutral"
}

# Scan files into train/val split lists
RAF_TRAIN, RAF_VAL = [], []
for lab_id, emo in LABEL_MAP.items():
    train_folder = os.path.join(RAF_ROOT, "train", lab_id)
    test_folder  = os.path.join(RAF_ROOT, "test",  lab_id)
    # check folders exist
    if not os.path.isdir(train_folder) or not os.path.isdir(test_folder):
        raise RuntimeError(f"Expected train/test under {RAF_ROOT}, but missing {lab_id}")

    # train split (~90% via hash)
    for p in glob.glob(f"{train_folder}/*.jpg"):
        if hash(p) % 10 == 0:
            RAF_VAL.append((p, emo))
        else:
            RAF_TRAIN.append((p, emo))

    # official test → include in validation
    for p in glob.glob(f"{test_folder}/*.jpg"):
        RAF_VAL.append((p, emo))

# Shuffle for randomness
random.shuffle(RAF_TRAIN)
random.shuffle(RAF_VAL)

# Sanity print counts
raf_train_counts = {}
for _, lbl in RAF_TRAIN:
    raf_train_counts[lbl] = raf_train_counts.get(lbl, 0) + 1
raf_val_counts = {}
for _, lbl in RAF_VAL:
    raf_val_counts[lbl] = raf_val_counts.get(lbl, 0) + 1

print("RAF-DB train counts:", raf_train_counts, "→ total:", len(RAF_TRAIN))
print("RAF-DB val   counts:", raf_val_counts,   "→ total:", len(RAF_VAL))
```

```
RAF-DB train counts: {'happy': 4297, 'neutral': 2285, 'anger': 642, 'sad': 1771, 'disgust': 641, 'surprise': 1158, 'fear': 249} → total: 11043
RAF-DB val   counts: {'happy': 1660, 'surprise': 461, 'sad': 689, 'neutral': 919, 'disgust': 236, 'anger': 225, 'fear': 106} → total: 4296
```

```
# Image transforms
train_tf = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.RandomHorizontalFlip(),
    transforms.ColorJitter(brightness=0.2, contrast=0.2),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                         [0.229, 0.224, 0.225])
])

val_tf = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                         [0.229, 0.224, 0.225])
])
```

Dataset Wrappers and DataLoader Setup

```
# Prepare a PathDataset & weighted sampler

# Dataset wrapper
class PathDataset(Dataset):
    def __init__(self, samples, transform, cls2idx):
        self.samples   = samples
        self.transform = transform
        self.cls2idx   = cls2idx
    def __len__(self):
        return len(self.samples)
```

```
    def __getitem__(self, idx):
        path, lbl = self.samples[idx]
        img = Image.open(path).convert("RGB")
        return self.transform(img), self.cls2idx[lbl]

# Combine FER+RAF train lists
full_train = FER_FILES + RAF_TRAIN

# Compute per-class weights
labels      = [lbl for _, lbl in full_train]
counts      = Counter(labels)
class_wts   = {cls: 1.0/count for cls, count in counts.items()}
sample_wts  = [class_wts[lbl] for _, lbl in full_train]

# Weighted sampler
sampler = WeightedRandomSampler(
    weights=sample_wts,
    num_samples=len(sample_wts),
    replacement=True
)

# Label-to-index mapping for training
CLS2IDX = {
    "anger": 0,
    "disgust": 1,
    "fear": 2,
    "happy": 3,
    "neutral": 4,
    "sad": 5,
    "surprise": 6
}

# Datasets & Loaders
train_ds   = PathDataset(full_train, train_tf, CLS2IDX)
val_ds     = PathDataset(RAF_VAL + [(p,lbl) for p,lbl in FER_FILES if hash(p)%10==0],
                         val_tf, CLS2IDX)  # simple val on RAF+FER val

train_loader = DataLoader(
    train_ds, batch_size=64, sampler=sampler,
    num_workers=8, pin_memory=True
)
val_loader = DataLoader(
    val_ds, batch_size=64, shuffle=False,
    num_workers=8, pin_memory=True
)
```

Model Definition and Optimizer Setup

```
# Instantiate MobileNetV2
device = "cuda"
mob = timm.create_model('mobilenetv2_100', pretrained=True, num_classes=7).to(device)
opt_m = optim.AdamW(mob.parameters(), lr=5e-4, weight_decay=1e-4)
sched_m = optim.lr_scheduler.CosineAnnealingLR(opt_m, T_max=15)
scaler_m = GradScaler()
crit_m = nn.CrossEntropyLoss(label_smoothing=0.1)
metric_m = MulticlassAccuracy(num_classes=7).to(device)
```

```
/usr/local/lib/python3.11/dist-packages/huggingface_hub/utils/_auth.py:94: UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab (https://huggingface.co/settings/tokens), set it as secret in your Google Colab and restart your session.
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to access public models or datasets.
  warnings.warn(
<ipython-input-11-1244901770>:6: FutureWarning: `torch.cuda.amp.GradScaler(args...)` is deprecated. Please use `torch.amp.GradScaler('cuda', args...)` instead.
  scaler_m = GradScaler()
```

Model Training and Validation Loop

```
# Train loop for MobileNetV2
best_m, patience = 0.0, 0
PATIENCE_M = 3

for epoch in range(1, 16):
    # Train
    mob.train()
    train_bar = tqdm(train_loader, desc=f"Mob E{epoch}", leave=False)
    for x,y in train_bar:
        x,y = x.to(device), y.to(device)
        with autocast():
            out = mob(x)
            loss = crit_m(out, y)
        opt_m.zero_grad(set_to_none=True)
        scaler_m.scale(loss).backward()
        scaler_m.step(opt_m); scaler_m.update()
        acc = (out.argmax(1)==y).float().mean().item()
        train_bar.set_postfix(loss=f"{loss.item():.3f}", acc=f"{acc:.3f}")

    # Validate
    mob.eval()
    val_loss = 0; val_acc = 0; n=0
    with torch.no_grad(), autocast():
        for x,y in val_loader:
            x,y = x.to(device), y.to(device)
            out   = mob(x)
            loss  = crit_m(out,y)
            val_loss += loss.item()*y.size(0)
            val_acc  += (out.argmax(1)==y).sum().item()
            n        += y.size(0)
    val_loss /= n; val_acc /= n

    print(f"Epoch {epoch:02d} → val_acc: {val_acc:.3f}, val_loss: {val_loss:.3f}")

    # Early stopping
    if val_acc > best_m:
        best_m, patience = val_acc, 0
        torch.save(mob.state_dict(), "/content/drive/MyDrive/models/mobV2FERplusRAFDB.pth")
    else:
        patience += 1
        if patience >= PATIENCE_M:
            print(f"↪ Mob early stop at epoch {epoch}")
            break
    sched_m.step()

print(f"Finished MobileNetV2, best val_acc = {best_m:.3f}")
```

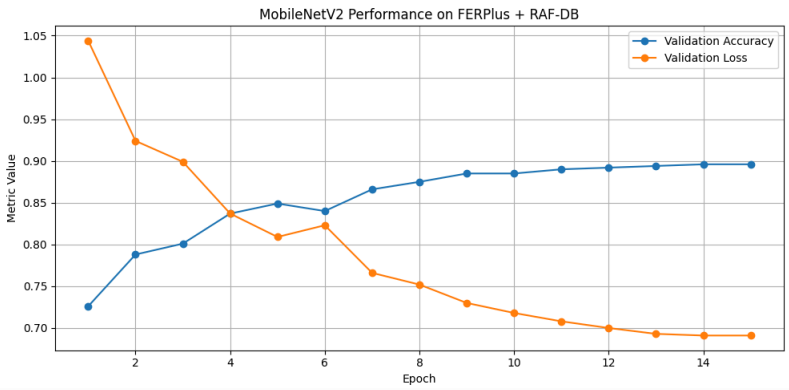
Show hidden output

```
#Visualize model's training history based on actual results

history = {
    'epoch': list(range(1, 16)),
    'val_acc': [0.726, 0.788, 0.801, 0.837, 0.849,
                0.840, 0.866, 0.875, 0.885, 0.885,
                0.890, 0.892, 0.894, 0.896, 0.896],
```

```
    'val_loss': [1.044, 0.924, 0.899, 0.837, 0.809,
                 0.823, 0.766, 0.752, 0.730, 0.718,
                 0.708, 0.700, 0.693, 0.691, 0.691]
}

plt.figure(figsize=(10, 5))
plt.plot(history['epoch'], history['val_acc'], label='Validation Accuracy', marker='o')
plt.plot(history['epoch'], history['val_loss'], label='Validation Loss', marker='o')
plt.title("MobileNetV2 Performance on FERPlus + RAF-DB")
plt.xlabel("Epoch")
plt.ylabel("Metric Value")
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()
```



Model Evaluation: Metrics and Confusion Matrix

```
# Compute how many batches in your validation set
BS    = val_loader.batch_size
N_val = len(FER_FILES) + len(RAF_VAL)
steps_val = math.ceil(N_val / BS)

# Gather predictions & true labels with a bounded loop
all_preds, all_lbls = [], []
mob.eval()
with torch.no_grad(), torch.amp.autocast(device_type="cuda"):
    for x, y in tqdm(
        islice(val_loader, steps_val),
        total=steps_val,
        desc="Evaluating MobileNetV2",
        ncols=80
    ):
        x, y    = x.to(device), y.to(device)
        logits  = mob(x)
        all_preds.append(logits.argmax(1).cpu().numpy())
        all_lbls.append(y.cpu().numpy())

preds  = np.concatenate(all_preds)
labels = np.concatenate(all_lbls)
EMOS = ['anger', 'disgust', 'fear', 'happy', 'neutral', 'sad', 'surprise']

# Print the classification report
print(classification_report(labels, preds, target_names=EMOS, digits=3))

# Plot the confusion matrix
cm = confusion_matrix(labels, preds, labels=range(len(EMOS)))
df_cm = pd.DataFrame(cm, index=EMOS, columns=EMOS)
plt.figure(figsize=(6,5))
sns.heatmap(df_cm, annot=True, fmt="d", cmap="Blues")
plt.xlabel("Predicted")
plt.ylabel("True")
plt.title("MobileNetV2 Confusion Matrix")
plt.show()
```

```
Evaluating M

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```
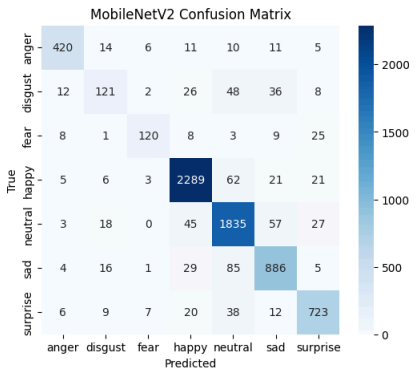

	precision	recall	f1-score	support
anger	0.917	0.881	0.898	477
disgust	0.654	0.478	0.553	253
fear	0.863	0.690	0.767	174
happy	0.943	0.951	0.947	2407
neutral	0.882	0.924	0.903	1985
sad	0.859	0.864	0.861	1026
surprise	0.888	0.887	0.888	815
accuracy			0.896	7137
macro avg	0.858	0.811	0.831	7137
weighted avg	0.894	0.896	0.894	7137



The final MobileNetV2 model achieved an overall validation accuracy of 89.6% with strong per-class performance. Emotions like 'happy', 'neutral', and 'surprise' showed F1-scores above 88%, while 'disgust' remained the most challenging, as expected from previous FER studies. These results confirm that the model generalizes well across datasets and is suitable for neuromarketing applications.

Save Trained Model for Import into Amazon SageMaker for Deployment

```
# Ensure the models directory exists
models_dir = "/content/drive/MyDrive/models"
os.makedirs(models_dir, exist_ok=True)

# Save the MobileNetV2 checkpoint
save_path = os.path.join(models_dir, "mobV2FERplusRAFDB.pth")
torch.save(mob.state_dict(), save_path)

print(f"✓ MobileNetV2 model saved to {save_path}")
```

```
✓ MobileNetV2 model saved to /content/drive/MyDrive/models/mobV2FERplusRAFDB.pth
```

```
# Save the full MobileNetV2 model
full_model_path = os.path.join(models_dir, "mobV2_full.pth")
torch.save(mob, full_model_path)

print(f"✓ Full MobileNetV2 model saved to {full_model_path}")
```

```
✓ Full MobileNetV2 model saved to /content/drive/MyDrive/models/mobV2_full.pth
```

Create and Save inference.py in Colab

```
inference_code = """
import torch
import torch.nn.functional as F
import torchvision.transforms as transforms
from PIL import Image
import io

def model_fn(model_dir):
    model = torch.load(f"{model_dir}/mobV2_full.pth", map_location="cpu")
    model.eval()
    return model

def input_fn(request_body, request_content_type):
    if request_content_type == "application/x-image":
        image = Image.open(io.BytesIO(request_body)).convert("RGB")
        transform = transforms.Compose([
            transforms.Resize((224, 224)),
            transforms.ToTensor(),
            transforms.Normalize([0.485, 0.456, 0.406],
                                 [0.229, 0.224, 0.225])
        ])
        return transform(image).unsqueeze(0)
    raise Exception("Unsupported content type: {}".format(request_content_type))

def predict_fn(input_data, model):
    with torch.no_grad():
        output = model(input_data)
        probs = F.softmax(output, dim=1)
    return probs

def output_fn(prediction, content_type):
    if content_type == "application/json":
        return prediction.numpy().tolist()
    raise Exception("Unsupported content type: {}".format(content_type))
"""
```

```
inference_path = "/content/drive/MyDrive/models/inference.py"
with open(inference_path, "w") as f:
    f.write(inference_code)

print(f"✓ Inference script saved to: {inference_path}")
```

```
✓ Inference script saved to: /content/drive/MyDrive/models/inference.py
```

```
!tar -czvf mobV2_model.tar.gz -C /content/drive/MyDrive/models mobV2_full.pth inference.py
```

```
mobV2_full.pth
inference.py
tar: inference.py: file changed as we read it
```

```
!tar -tzvf mobV2_model.tar.gz
```

```
-rw------- root/root   9227896 2025-06-16 23:16 mobV2_full.pth
-rw------- root/root      1153 2025-06-16 23:21 inference.py
```

Model training and packaging complete. The model is now ready to be imported and deployed in Amazon SageMaker!