FACECOM Technical Summary: Gender Classification & Robust Face Recognition

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Overview

This project addresses the dual objectives of the **FACECOM** challenge: (A) Gender classification and (B) Face recognition under distortions. A unified deep learning pipeline was implemented using TensorFlow and pre-trained models on Google Colab.

Dataset

FACECOM contains 5K+ face images under conditions like blur, fog, low light, and glare. Annotations include gender (binary) and identity (multi-class). Splits: 70% train, 15% validation, 15% test (hidden).

Approach

Task A – Gender Classification:

- Custom CNN and VGG-based transfer learning pipeline.
- Class weights address male-dominated imbalance.
- Augmentation: rotation, zoom, shift, flip, brightness.
- Two-stage training: freeze pretrained layers, then fine-tune.

Task B – Face Recognition:

- EfficientNetB2 backbone fully fine-tuned.
- Unified training on both clear and distorted images.
- Stratified train-test split with distortion-aware input.
- Dropout and augmentation ensure generalization.

Architecture

Task A: VGG16 → Flatten → Dense(256) → Dropout(0.5) → Sigmoid
Task B: EfficientNetB2 → GlobalAvgPool → Dropout(0.3) → Dense(#IDs, Softmax)

Results

Task A – Gender Classification

- **Training:** Accuracy: 0.93, Precision: 0.93, Recall (macro): 0.93, F1 (macro): 0.93
- **Validation:** Accuracy: 0.91, Precision: 0.86, Recall (macro): 0.84, F1 (macro): 0.85

Task B – Face Recognition

- Top-1 Accuracy: **0.9952**
- Precision (macro): **0.9963**, Recall (macro): **0.9954**, F1 (macro): **0.9953**

Conclusion

This unified pipeline achieves strong performance across both semantic and identity-level face tasks in challenging conditions. Future work includes improving gender classification fairness and deploying lightweight models for real-time inference.