Gender Classification from Facial Images

1. Dataset Description and Preprocessing

The UTKFace dataset was used for this project. It contains over 20,000 facial images annotated with age, gender, and race. For this lab, only the gender attribute was used, where 0 represents Male and 1 represents Female. Images were provided in JPG format with varying resolutions and lighting conditions.

Preprocessing steps included loading images, resizing them to a fixed resolution (64x64 or 128x128 for transfer learning), converting color channels to RGB, and normalizing pixel values to the range [0,1]. The dataset was then split into training, validation, and testing sets using stratified sampling to preserve class balance.

2. Model Architecture Rationale

Two approaches were implemented: a custom CNN model and transfer learning models using MobileNetV2 and VGG16. The custom CNN was designed with convolutional layers, max pooling, and dropout to reduce overfitting. It is lightweight and suitable for learning fundamental facial features.

MobileNetV2 was selected due to its efficiency and suitability for real-time applications. VGG16 was included as a heavier alternative to compare performance. Pre-trained ImageNet weights allowed the models to leverage learned visual features, improving accuracy and reducing training time.

3. Training Curves and Performance Metrics

Training and validation accuracy and loss were monitored across epochs. Early stopping and learning rate reduction were applied to avoid overfitting. The MobileNetV2 model achieved the best balance between accuracy and efficiency.

Performance was evaluated using accuracy on the test dataset. The transfer learning models outperformed the custom CNN, demonstrating the advantage of pre-trained architectures.

4. Discussion of Results and Limitations

The results show that deep learning models can effectively classify gender from facial images. Transfer learning significantly improved performance compared to training from scratch. MobileNetV2 provided high accuracy with lower computational cost.

Limitations include dataset bias, as gender classification is limited to binary labels. Variations in lighting, occlusion, and facial expressions may also affect performance. Additionally, ethical concerns should be considered when deploying facial recognition systems.

5. Answers to Discussion Questions

1. Why normalization is important: It ensures stable and faster model convergence.
2. Why transfer learning performs better: Pre-trained models already capture rich features.
3. Effect of overfitting: Addressed using dropout and early stopping.
4. Why MobileNetV2 is preferred for deployment: Lightweight and fast inference.