Gender, Age, and Ethnicity Classification Using Multi-Task Learning

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Abstract

This project introduces a multitask deep learning framework designed to simultaneously predict gender, age group, and ethnicity from facial images. Leveraging the FairFace dataset, we developed a Convolutional Neural Network (CNN) that integrates Depthwise Separable Convolutions to enhance computational efficiency while maintaining high accuracy. The pipeline initiates with face detection and cropping using Haar cascades, followed by feature extraction through a lightweight multitask architecture. Comprehensive evaluations were conducted to assess and mitigate potential biases across different demographic groups, ensuring fairness and inclusivity in model predictions. The trained model is deployed via Streamlit, demonstrating its applicability in diverse real-world scenarios such as security, marketing analytics, and social research.

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1. Introduction

The surge in demand for automated human profiling systems has propelled significant advancements in computer vision and deep learning technologies. Accurately predicting demographic attributes—namely gender, age group, and ethnicity—from facial images holds substantial value across various sectors, including marketing analytics, healthcare diagnostics, and security surveillance. This project aims to develop a robust multitask learning framework utilizing Convolutional Neural Networks (CNNs) to deliver precise predictions of these demographic factors.

Multitask learning presents several advantages over traditional single-task models. By sharing feature representations across related tasks, multitask frameworks not only enhance prediction accuracy but also reduce computational complexity and improve model generalizability. This synergy allows for more efficient training and better performance, particularly in scenarios with limited labeled data.

The project encompasses three primary areas:

1. **Face Detection and Preprocessing**: Utilizing Haar cascades for accurate face detection and image cropping.

2. **Demographic Prediction**: Implementing a lightweight multitask CNN architecture to predict gender, age group, and ethnicity concurrently.

3. **Model Deployment**: Developing a user-friendly application using Streamlit to demonstrate the model's real-world applicability.

While the focus is on demographic attribute classification, broader applications such as emotion recognition and face identification are beyond the scope of this study.

2. Literature Review

2.1. Metrics for Evaluating Data Imbalance

The challenge of data imbalance has been extensively studied in the field of machine learning, as it can significantly impact model performance, particularly for classification tasks. To address this issue, various metrics have been proposed to quantitatively assess the degree of imbalance in datasets. This section reviews key metrics commonly used in literature:

2.1.1. Max Ratio and Min Ratio

These metrics quantify the imbalance by comparing the maximum and minimum proportions of class frequencies. The **max ratio** is the proportion of the largest class relative to the total dataset size, while the **min ratio** measures the smallest class's proportion. Together, they highlight the spread of class distributions and are simple yet effective for identifying extreme imbalance scenarios.

Let the dataset have C classes, and let N_c be the number of instances in class c. The total number of instances is denoted as $N = \sum_{c=1}^{C} N_c$. Then the **max ratio** and **min ratio** can be defined as:

$$\text{Max Ratio} = \frac{\max(N_c)}{N}$$

$$\text{Min Ratio} = \frac{\min(N_c)}{N}$$

2.1.2. Ratio Range

The ratio range, computed as the difference between the max and min ratios, provides a straightforward measure of the variability in class proportions. A higher ratio range indicates greater disparity among classes, which could lead to biased model predictions.

$$\text{Ratio Range} = \text{Max Ratio} - \text{Min Ratio}$$

2.1.3. Coefficient of Variation (CV)

The **coefficient of variation** (CV) measures the relative variability of class frequencies, calculated as the standard deviation normalized by the mean class frequency. It captures the extent of imbalance relative to the average class size, with higher values indicating more pronounced imbalance.

Let the frequencies of the C classes be $N_1, N_2, \ldots, N_C$. The mean class frequency μ and the standard deviation σ are defined as:

$$\mu = \frac{1}{C} \sum_{c=1}^{C} N_c$$

$$\sigma = \sqrt{\frac{1}{C} \sum_{c=1}^{C} (N_c - \mu)^2}$$

The **coefficient of variation** is then:

$$\mathrm{CV} = \frac{\sigma}{\mu}$$

2.1.4. Entropy

Entropy quantifies the uncertainty or diversity in class distributions. A perfectly balanced dataset has maximum entropy, while a highly imbalanced dataset has lower entropy. Entropy is particularly useful for multi-class problems, where it provides an aggregated view of imbalance.

Entropy H for a multi-class dataset is defined as:

$$H = -\sum_{c=1}^{C} p_c \log(p_c)$$

where $p_c = \frac{N_c}{N}$ is the proportion of class c in the dataset.

2.1.5. Gini Index

The **Gini index**, commonly used in economics to measure inequality, has been adapted to evaluate imbalance in machine learning. It ranges from 0 (perfect balance) to 1 (complete imbalance), capturing the inequality in class frequencies. The Gini index G is defined as:

$$G = 1 - \sum_{c=1}^{C} p_c^2$$

where $p_c = \frac{N_c}{N}$ is the proportion of class c in the dataset.

2.2. Face Analysis Techniques

Face analysis has been a significant research area in computer vision, evolving from traditional methods to state-of-the-art deep learning-based approaches. Early techniques relied heavily on handcrafted features, such as Haar cascades [9] and Local Binary Patterns (LBP) [10] , which were effective for simple tasks like face detection and basic feature extraction. Haar cascades, introduced by Viola and Jones (2001), revolutionized real-time face detection by using an integral image representation and a cascaded classifier structure. LBP further contributed to texture-based face representation by encoding local image patterns.

With the advent of deep learning, Convolutional Neural Networks (CNNs) have emerged as the standard for face analysis tasks due to their ability to automatically learn hierarchical feature representations from raw pixel data. CNN-based architectures like AlexNet, VGG, and ResNet have demonstrated superior performance in tasks such as face detection, recognition, and attribute classification. Advanced face analysis frameworks now integrate facial landmarks for alignment and preprocessing to improve accuracy. Techniques like the Single Shot Multibox Detector (SSD) and Multi-Task Cascaded Convolutional Networks (MTCNN) have also been adopted for robust face detection under varying conditions of lighting, pose, and occlusion.

Recent trends emphasize fairness and explainability in face analysis, as traditional models have often shown bias against underrepresented demographic groups. The shift toward datasets and methods that account for demographic diversity has become crucial in reducing these disparities.

2.3. Multitask Learning

Multitask learning (MTL) is a paradigm in which a model is trained to optimize multiple objectives simultaneously. By sharing a common feature representation across tasks, MTL improves generalization and reduces computational overhead. This approach has shown remarkable success in domains like facial attribute analysis, emotion detection, and biometric verification.

Caruana (1997) [13] introduced MTL as a method to improve generalization by leveraging the domain-specific information contained in the training signals of related tasks. In the context of face analysis, MTL is particularly advantageous because facial features such as eyes, nose, and mouth provide shared information relevant to multiple tasks like gender classification, age estimation, and ethnicity prediction.

Research has demonstrated that MTL can mitigate overfitting, especially when labeled data is limited. Studies by Ranjan et al. (2017) highlight that MTL frameworks achieve state-of-the-art performance by balancing task-specific losses with a shared feature extractor. Moreover, task interdependence plays a critical role; for instance, learning age and gender together can improve the prediction accuracy of both tasks, as they share biological and social correlations.

Advanced implementations of MTL employ attention mechanisms and task-specific adapters to manage conflicts between tasks with varying levels of complexity or data availability. These methods further refine the shared representation to maximize task performance without sacrificing generalizability.

2.4. FairFace Dataset

The FairFace dataset [1] represents a significant advancement in addressing bias in face analysis datasets. Traditional datasets like LFW (Labeled Faces in the Wild) and CelebA, while widely used, often exhibit skewed distributions, overrepresenting certain demographic groups (e.g., white males) while underrepresenting others. Such biases lead to models that perform poorly on underrepresented groups, raising concerns about fairness and equity in automated systems.

FairFace, introduced by Karkkainen and Joo (2021) [1], addresses these challenges by providing a balanced dataset annotated for gender, age, and ethnicity across seven racial groups. This diversity ensures that models trained on FairFace are better equipped to generalize across different demographic groups, reducing performance disparities.

The dataset contains around 100,000 high-quality face images with labels for attributes such as race (White, Black, Indian, East Asian, Southeast Asian, Middle Eastern, and Latino), gender (Male and Female), and age (seven age groups). It has been widely adopted in research and commercial applications for training fair and unbiased models. Studies using FairFace have shown improved fairness metrics, such as equalized odds and demographic parity, in tasks ranging from facial recognition to demographic attribute classification.

By addressing the limitations of earlier datasets, FairFace not only promotes ethical AI practices but also enables researchers to build robust systems applicable to diverse populations. Its balanced representation has made it a benchmark for fairness in face analysis tasks.

3. Methodology

3.1. Dataset

The FairFace dataset [1], introduced by Kärkkäinen and Joo (2021), is a large-scale facial dataset designed to address biases that exist in many facial recognition and demographic classification datasets. Traditional datasets, such as CelebA and LFW, often suffer from biases in representation, which can lead to suboptimal performance on underrepresented demographic groups. The FairFace dataset was created to mitigate this issue by ensuring balanced representation across multiple demographic groups, including racial, gender, and age categories.

3.1.1. Dataset Overview

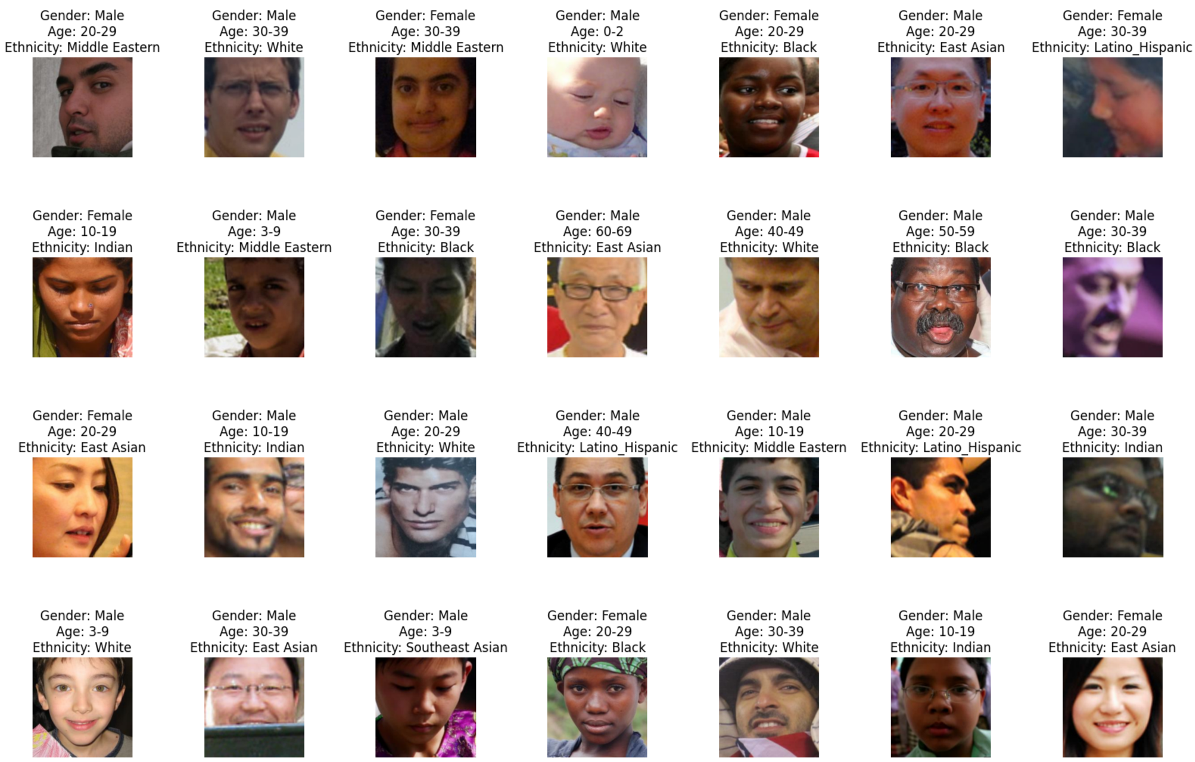

Figure 3.1: Sample Images from FairFace Dataset

The FairFace dataset contains around 100,000 images of faces, with annotations for gender, age group, and ethnicity. The images are sourced from the YFCC-100M dataset, ensuring diversity in the facial characteristics represented. This dataset provides a critical resource for building AI systems that are not only accurate but also fair and ethical.

- Race/Ethnicity: Seven categories – White, Black, Indian, East Asian, Southeast Asian, Middle Eastern, and Latino.
- Gender: Male and Female.
- Age: Nine age groups – `"0-2"`, `"3-9"`, `"10-19"`, `"20-29"`, `"30-39"`, `"40-49"`, `"50-59"`, `"60-69"` and `"70+"`.

3.1.2. Key Features

- **Balanced Representation**: Unlike many other face datasets that have a skewed representation of certain groups, FairFace ensures an equal distribution of images across the seven racial/ethnic groups, promoting fairness in facial recognition and demographic prediction tasks.
- **High-Quality Annotations**: Each image is labeled with gender, age group, and ethnicity by multiple annotators to ensure accuracy and consistency in the data.
- **Focus on Fairness**: FairFace is specifically designed to help reduce the biases that often occur in machine learning models by providing a balanced and diverse dataset, making it an important tool for training more inclusive and fair AI systems.

3.1.3. Comparison with other datasets

Dataset	# Faces	In-the-wild?	Age	Gender	Ethnicity	Balanced?	White	Asian	Black
FairFace	108K	Yes	Yes	Yes	7 Categories	Yes	Yes	E, SE	Yes
UTKFace	20K	Yes	Yes	Yes	Merged	Yes	Yes	Merged	Yes
LFW+	15K	Yes	Yes	Yes	Merged	No	Yes	Merged	Yes
IMDB-WIKI	500K	Yes	Yes	Yes	No	No	Yes	No	No
MORPH	55K	Yes	Yes	Yes	Merged	No	Yes	No	Yes
FotW	25K	Yes	Yes	Yes	No	Yes	Yes	No	No
CACD	160K	Yes	Yes	No	No	No	Yes	No	No
CelebA	200K	Yes	No	Yes	Merged	No	Yes	No	No

Table 3.1: Comparison of FairFace Dataset with Other Public Face Datasets. Sources: FairFace [1], UTKFace [2], LFW+ [3], IMDB-WIKI [4], MORPH [5], FotW [6], CACD [7], CelebA [8].

3.2. Preprocessing

Proper preprocessing is crucial for ensuring the dataset is suitable for model training.

3.2.1. Data Loading and Preparation

The facial images were loaded using their file paths specified in the dataset's annotation file. The images were opened using the Python Imaging Library (PIL) and converted to the RGB color format to maintain consistency in input channels, essential for CNN processing.

3.2.2. Data Transformations

To prepare the images for training, a transformation pipeline was applied using PyTorch's `transforms` module. This pipeline consisted of the following:

- **Tensor Conversion:** The images were converted from their original PIL format into PyTorch tensors. This process scaled pixel values from their original range of $[0, 255]$ to $[0, 1]$, ensuring better numerical stability during training.
- **Normalization:** The pixel values of the images were standardized using channel-wise mean and standard deviation values derived from the ImageNet [11] dataset:
  - **Mean:** $[0.485, 0.456, 0.406]$
  - **Standard Deviation:** $[0.229, 0.224, 0.225]$

Label Mapping

The dataset contained categorical labels for gender, age, and ethnicity, which were encoded into numerical values for compatibility with the model. The mappings were as follows:

- **Gender Mapping:**
  - `Male` $\rightarrow 0$, `Female` $\rightarrow 1$
- **Age Group Mapping:** The age groups (e.g., `"0-2"`, `"3-9"`, etc.) were mapped to integer values ranging from 0 to 8, effectively representing ordinal age groups.
- **Ethnicity Mapping:** Seven ethnicity categories (e.g., `"White"`, `"Black"`, etc.) were mapped to integers ranging from 0 to 6, ensuring compatibility with the model's output layer for ethnicity classification.

Output Format

Each preprocessed image, along with its corresponding labels for gender, age, and ethnicity, was returned as a tuple in the form:

$$(\text{image}, (\text{gender label}, \text{age group label}, \text{ethnicity label}))$$

This structure enabled efficient multitask learning, where the model shared input features but had separate outputs for each task.

Validation Data Preprocessing

For the validation dataset, the same transformation pipeline was applied. The images underwent tensor conversion and normalization to ensure consistency between training and validation data.

3.3. Model Architecture

The proposed model, **LightweightMTLNet224**, is a compact and efficient multitask neural network designed to simultaneously predict *gender*, *age group*, and *ethnicity* from facial images. The architecture is tailored for resource-constrained environments by leveraging **Depthwise Separable Convolutions**, a computationally efficient alternative to standard convolution operations. Below is a detailed description of the model's components:

3.3.1. Depthwise Separable Convolution

The architecture incorporates **Depthwise Separable Convolution** [12] layers, which break down a standard convolution into two operations:

- **Depthwise Convolution**: Applies individual filters to each input channel independently, reducing computational overhead.
- **Pointwise Convolution**: Combines the outputs of the depthwise convolution across channels using a 1×1 kernel.

Each of these convolutional steps is followed by **Batch Normalization** for feature scaling and a **ReLU activation function** for introducing non-linearity. This efficient design allows for the extraction of spatial and channel-specific features at reduced computational cost.

3.3.2. Convolutional Layers

The model includes seven convolutional layers (Conv1 through Conv7), each progressively increasing feature depth and reducing spatial dimensions:

- **Conv1**: The input RGB image of size $224 \times 224 \times 3$ is processed into 64 feature maps.
- **Conv2 & Conv3**: These layers expand the feature maps to 128 channels.
- **Conv4 & Conv5**: Further increase the feature representation depth to 256 channels.
- **Conv6 & Conv7**: Extract high-level features with 512 channels.

These layers provide a hierarchical feature extraction pipeline, enabling the model to capture both low-level and high-level features from input images.

3.3.3. Pooling Layer

The model includes an **adaptive average pooling layer**, which reduces the spatial dimensions of the feature maps to 1×1. This layer provides a compact representation of the global features extracted by the convolutional layers, ensuring a fixed-size input for subsequent fully connected layers.

3.3.4. Fully Connected Layers

The output of the pooling layer is flattened and passed through:

- A **shared fully connected (FC) layer** with 256 neurons, which provides a common feature representation for all tasks. This layer uses a **ReLU activation function** for non-linearity.
- **Task-Specific Classifiers**:
  - A **gender classifier** predicting probabilities for two classes (male and female).
  - An **age group classifier** predicting probabilities for nine age groups.
  - An **ethnicity classifier** predicting probabilities for seven ethnic groups.

3.3.5. Multitask Outputs

The model's multitask learning framework ensures efficient feature sharing across tasks, while task-specific heads allow for specialization in gender, age group, and ethnicity predictions.

3.3.6. Pipeline Summary

1. The input image passes sequentially through seven convolutional layers (Conv1 to Conv7).
2. A global average pooling layer reduces the spatial dimensions of the feature maps.
3. The resulting features are passed through a shared fully connected layer.
4. Finally, task-specific classifiers output predictions for gender, age group, and ethnicity.

3.3.7. Advantages of the Architecture

- **Computational Efficiency**: The use of depthwise separable convolutions significantly reduces the number of parameters and computational complexity.
- **Compact Design**: The lightweight structure makes the model suitable for deployment on edge devices.
- **Multitask Learning**: Efficiently utilizes shared features while maintaining specialization across tasks.

3.4. Model Training

For our purpose of training the model for two gender classes, nine age groups and seven ethnicities the model comprised of 668077 trainable parameters.

The training procedure for the **LightweightMTLNet224** model involves training the model for a set number of epochs, during which the model learns to predict the three tasks: gender, age group, and ethnicity from facial images. The procedure is as follows:

3.4.1. Training and Validation Data

- Training set: $\sim$ 85,000 images
- Validation set: $\sim$ 11,000 images

Training Data

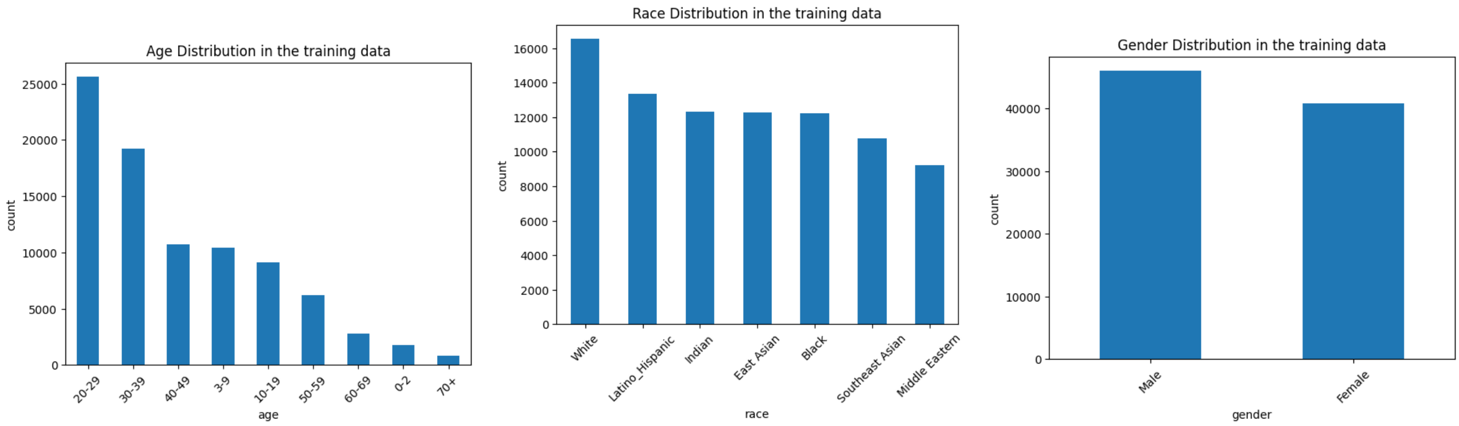

Figure 3.2: Distributions in the Training Data: Age, Ethnicity, and Gender.

The training data has significantly more people in the age group of `"20-29"` and `"30-39"`, the numbers are about the same for `"40-49"`, `"3-9"` and `"10-19"` (around 10000). For the age groups `"60-69"`, `"0-2"` and `"70+` the number of individuals is significantly less than 5000.

The distribution is fairly uniform across gender and Ethnicity. With both genders being almost equal and there is much significant variation in the number of people in different ethnicities.

	Max Ratio	Min Ratio	Ratio Range	Coefficient of Variation	Entropy	Gini Index
Age	0.295098	0.009707	0.285391	0.808729	2.695531	0.816217
Gender	0.530135	0.469865	0.060269	0.060269	0.997378	0.498184
Race	0.190526	0.106244	0.084282	0.169074	2.787104	0.853059

Table 3.2: Data Imbalance for Age, Gender, and Ethnicity in the training data

Figure 3.3: Distribution of Gender across age and ethnicity in training data

The distribution of gender is also fairly uniform across most age groups except 40-69 with significantly more males. It is also fairly even across all the ethnicity groups except Middle Eastern, where there are significantly more males than females.

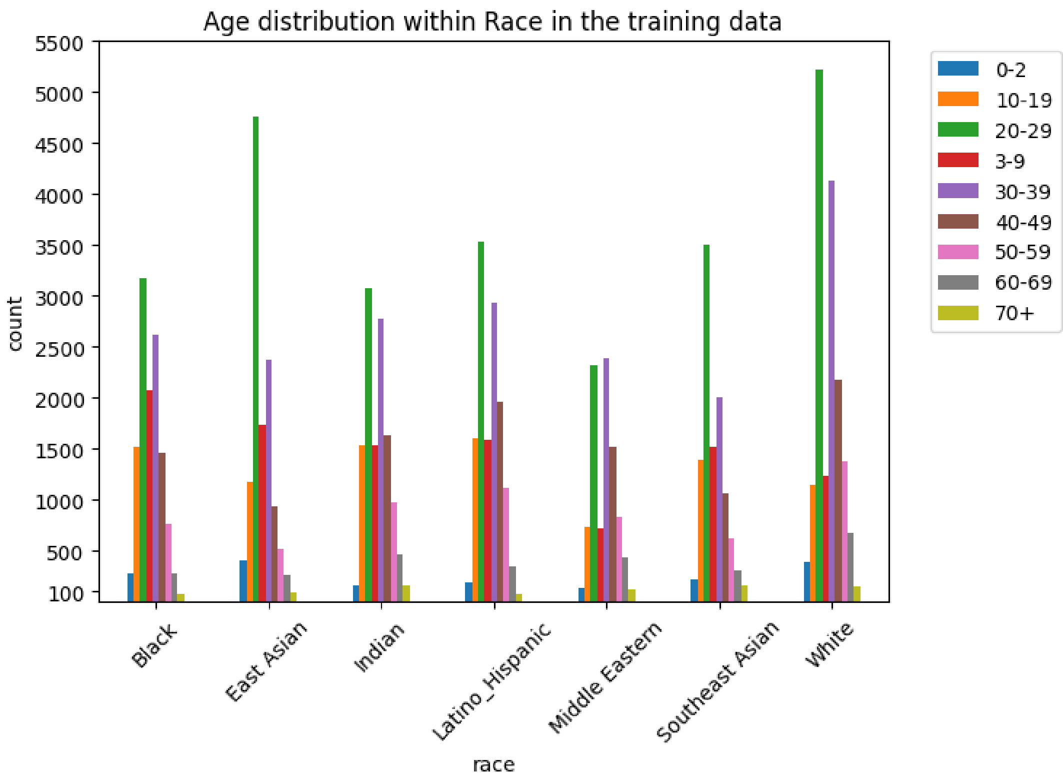

Figure 3.4: Distribution of age across ethnicity in the training data

The distribution of age groups between ethnicities is similar for all the ethnicity groups. Similar pattern is also observable in the distribution of ethnicities between age groups.

Validation Data

The distribution of gender, age groups and ethnicities in the validation data is almost identical to the training data. This is also easily observable for the distribution of gender across age groups and ethnicities as well as distribution of ethnicities across age groups.

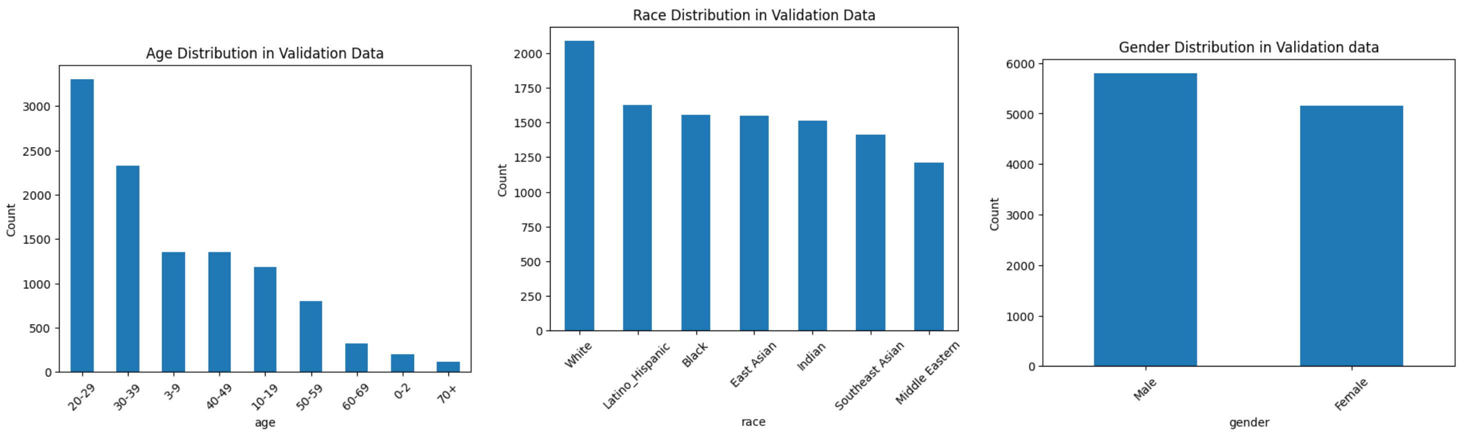

Figure 3.5: Distributions in the Validation Data: Age, Ethnicity, and Gender.

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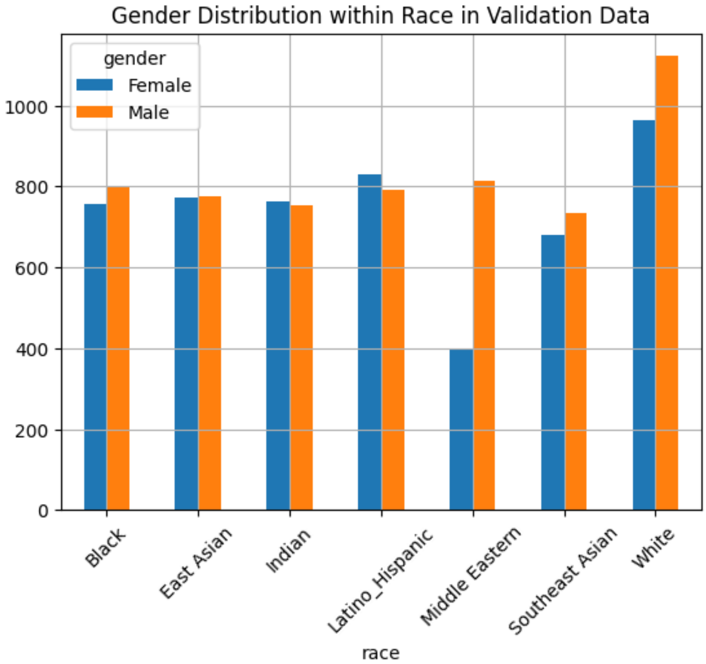
Table 3.3: Data Imbalance for Age, Gender, and Ethnicity in the validation data



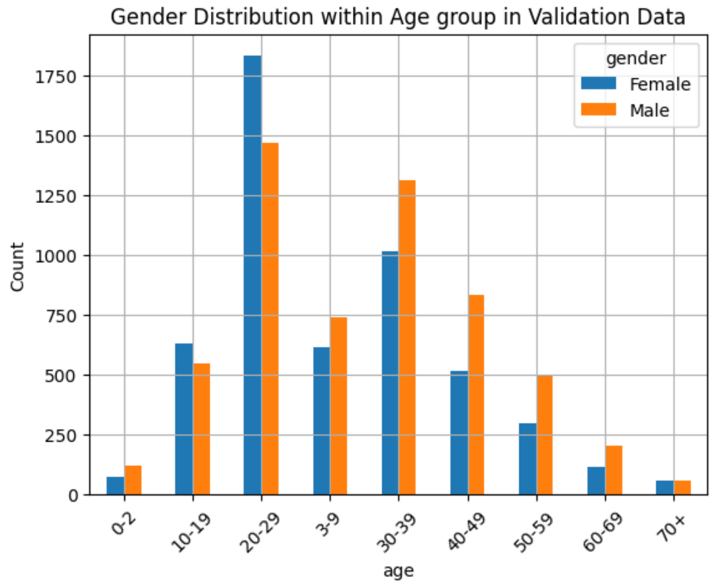


Figure 3.6: Distribution of Gender across age and ethnicity in validation data

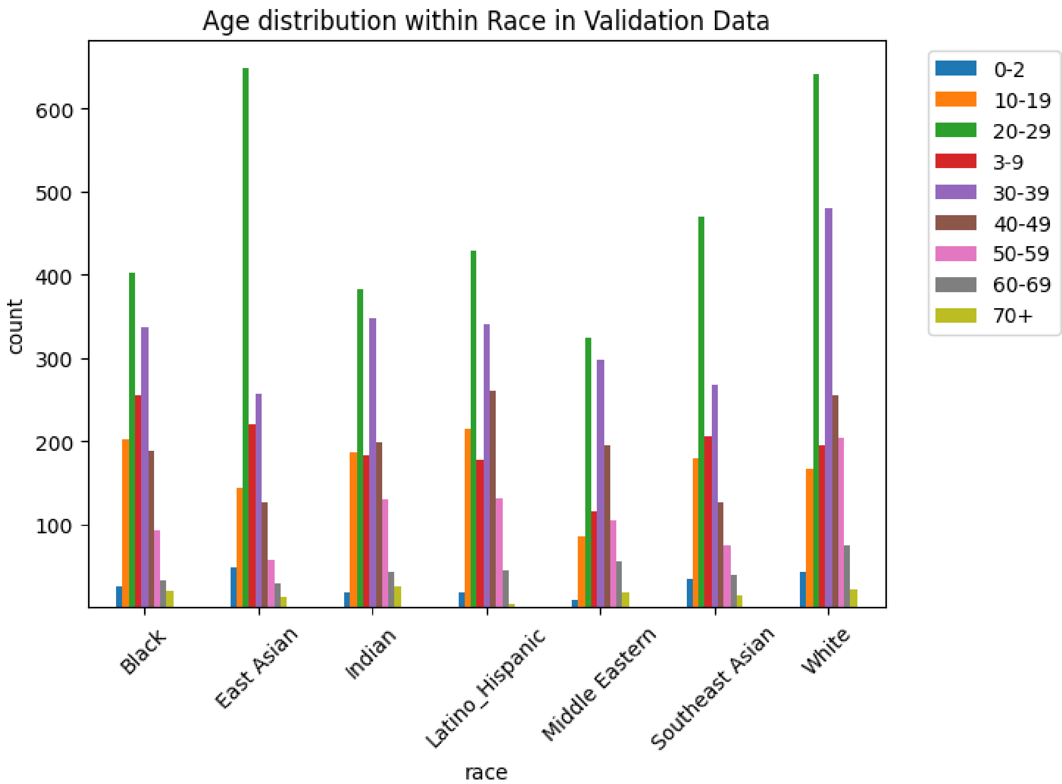


Figure 3.7: Distribution of age acorss ethnicity in validation data

3.4.2. Loss Functions

For each of the three tasks (gender, age, and ethnicity), we utilize the `CrossEntropyLoss` function. This loss function is appropriate for multi-class classification tasks, where the goal is to minimize the difference between the predicted and actual class labels. The loss functions for the three tasks are defined as follows:

- **Gender Loss:** A `CrossEntropyLoss` is used to minimize the error between the predicted and actual gender labels.
- **Age Loss:** A `CrossEntropyLoss` is employed to minimize the error between the predicted and actual age group labels.
- **Ethnicity Loss:** A `CrossEntropyLoss` is used to minimize the error between the predicted and actual ethnicity labels.

3.4.3. Optimizer

We use the Adam optimizer with a learning rate of 0.001 to update the model's weights during training. Adam is a popular choice due to its adaptive learning rate and efficient performance in training deep learning models.

- **Optimizer:** Adam
- **Learning Rate:** 0.001

3.4.4. Training Loop

The model was trained for up to 10 epochs with early stopping based on training loss improvement:

Epoch Steps

1. Set model to training mode.
2. Iterate over mini-batches:
    - Load images and labels to GPU.
    - Zero optimizer gradients.
    - Forward pass through the model.
    - Compute individual and total loss.
    - Backpropagate and update weights.
    - Monitor and print loss every 200 batches.
3. Evaluate on the validation set at each epoch end.
4. Implement early stopping if loss improvement is below 0.1.

3.4.5. Early Stopping

To prevent overfitting, training was halted if the decrease in training loss between consecutive epochs was less than 0.1.

3.4.6. Monitoring and Evaluation

During training, losses for each task were tracked and averaged per epoch for both training and validation sets. Metrics reported included:

- **Training Loss:**
- **Gender Loss:**
- **Age Loss:**
- **Ethnicity Loss:**

3.5. Model Deployment

The trained model was deployed using Streamlit, enabling interactive and user-friendly access to demographic predictions.

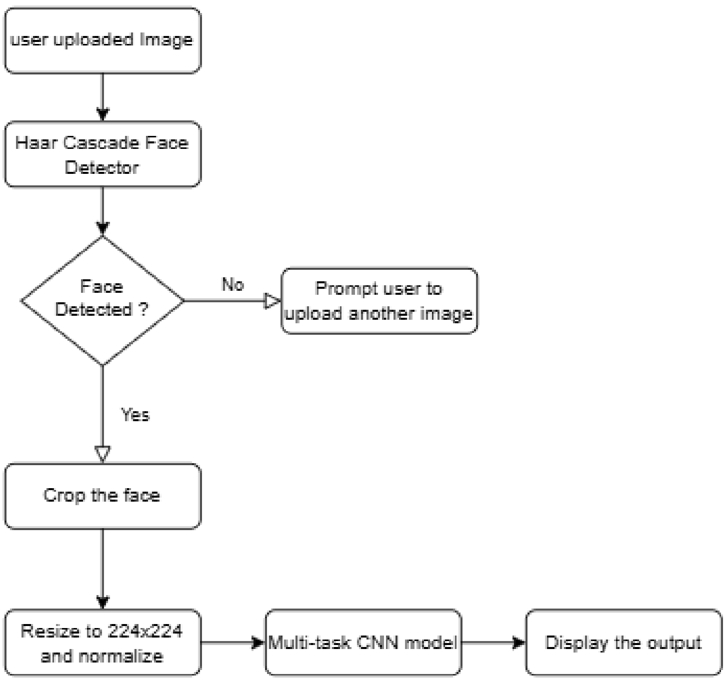


Figure 3.8: Model Pipeline

3.5.1. Model Pipeline

1. **Model Loading**:

   Load the pre-trained model from a .pth file and set it to evaluation mode.

2. **Face Detection**:

   Use a pre-trained Haar Cascade classifier to detect and crop faces in uploaded images. If no face is detected, the user is prompted to upload another image.

3. **Image Preprocessing**:

   Resize images to 224×224 pixels, convert to tensors, and normalize using ImageNet statistics.

4. **Prediction**:

   Pass the processed image through the model to obtain gender, age group, and ethnicity probabilities.

5. **Display Results**:

   Present the original image alongside predicted labels and probability distributions via bar charts.

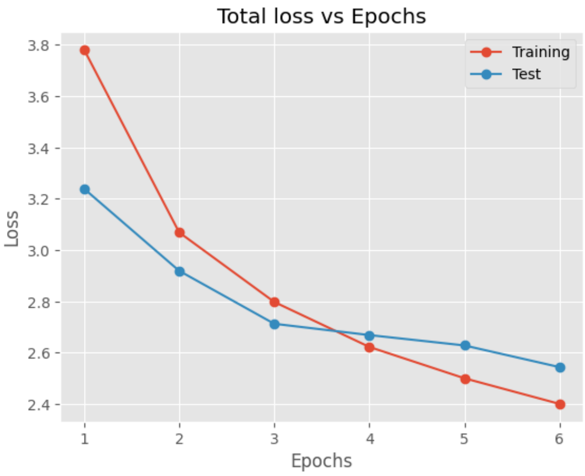
3.5.2. Technology Stack

The following technologies were used for the model deployment:

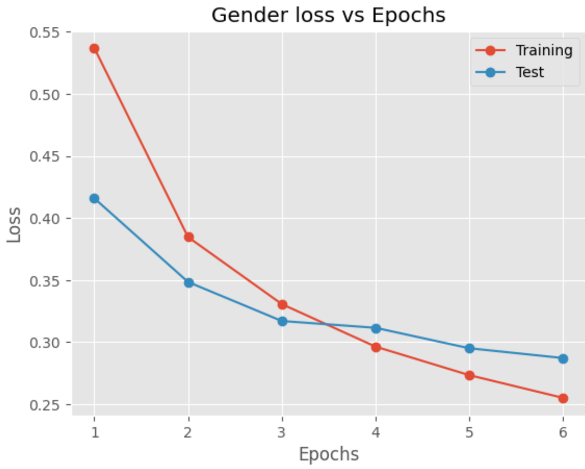
- **Streamlit**: For building the web application interface.
- **PyTorch**: For implementing and deploying the CNN model.
- **OpenCV**: For face detection using Haar Cascades.
- **Matplotlib**: For visualizing prediction probabilities.
- **NumPy and PIL**: For image manipulation and processing.

4. Results and Discussion

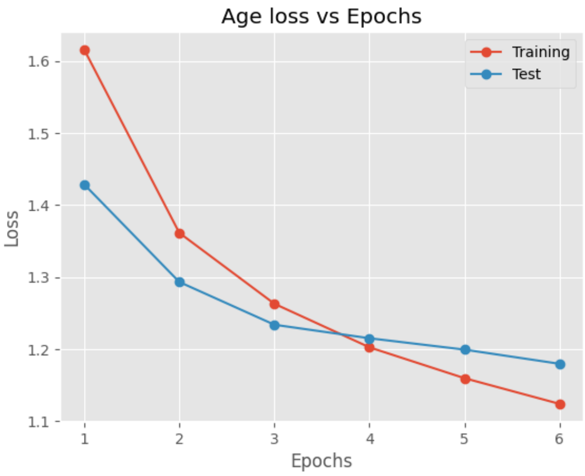
4.1. Training Performance



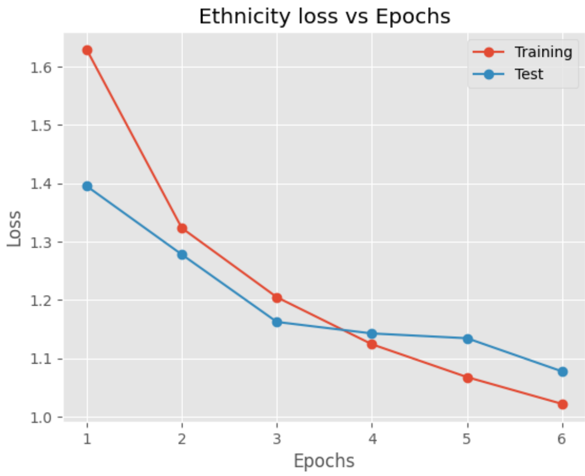
(a) Total Loss



(b) Gender Loss



(c) Age Loss



(d) Race Loss

Figure 4.1: Training losses for different aspects of our model.

The training process concluded after six epochs due to the early stopping criterion. Both training and validation losses stabilized, indicating that the model achieved a balance between learning and generalization.

4.2. Classification Accuracy

The model's accuracy metric across tasks are summarised below:

Task	Accuracy
Gender prediction	87.35%
Ethnicity prediction	59.33%
Age group prediction	50.83%

Table 4.1: Model accuracy accross tasks

4.3. Confusion Matrices

Confusion matrices provide deeper insights into the model's performance:

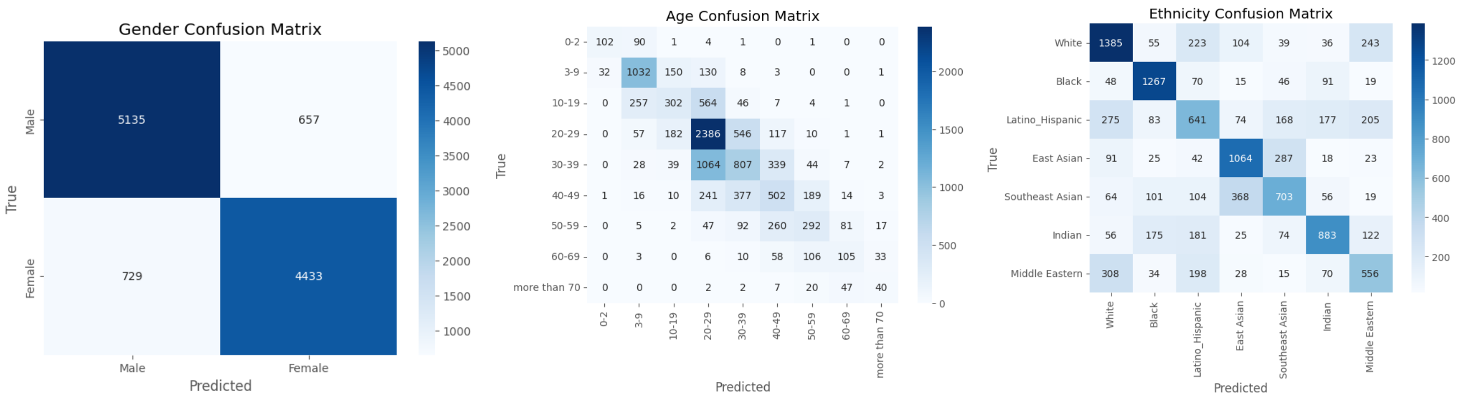


Figure 4.2: Confusion matrices for Gender, Age and Ethnicity

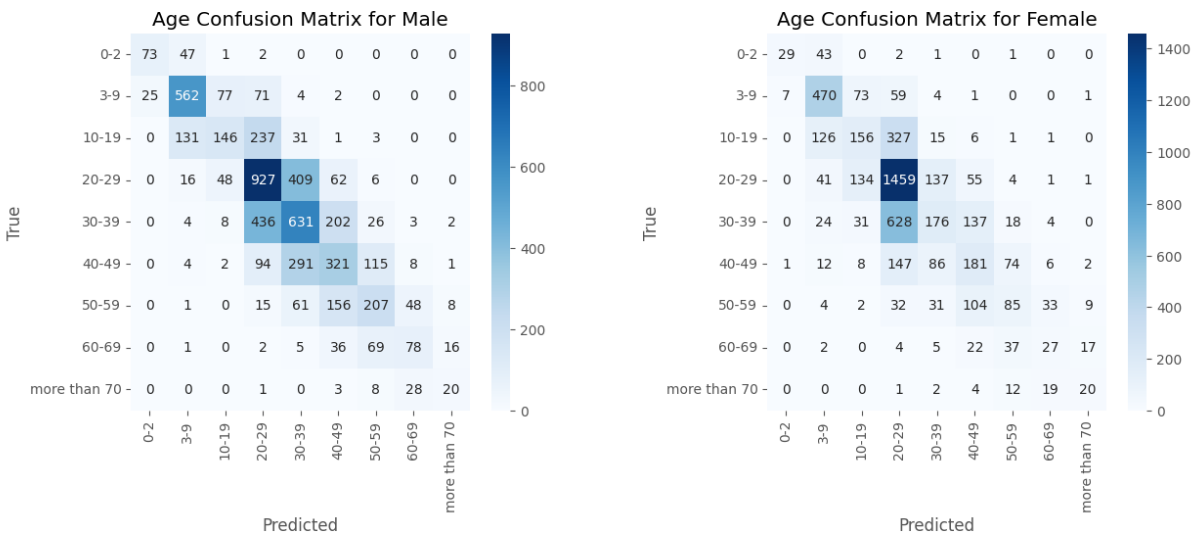


Figure 4.3: Age Confusion Matrices across gender

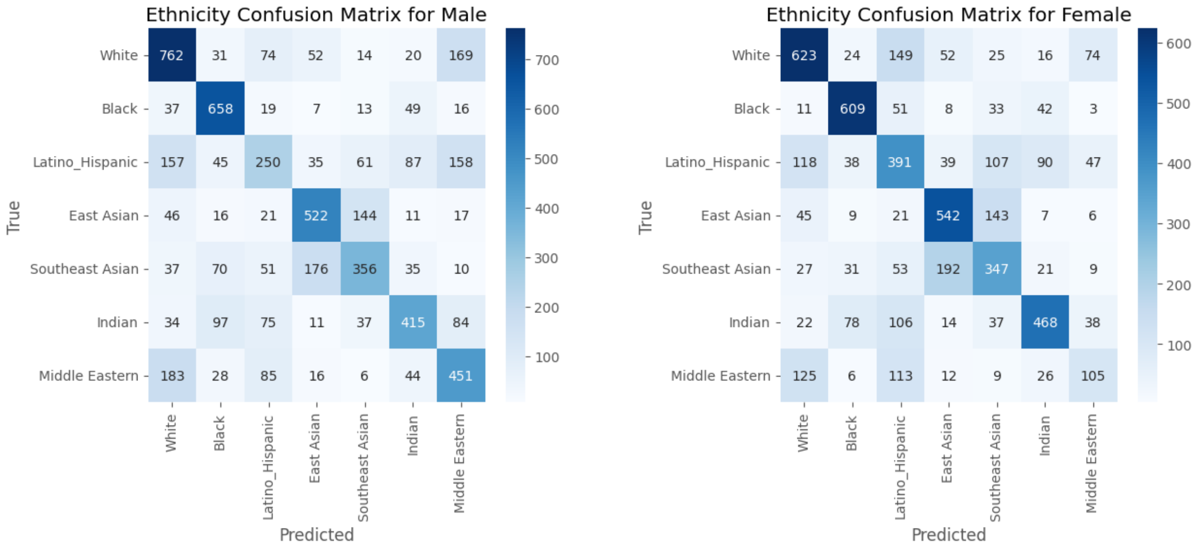


Figure 4.4: Race Confusion Matrices across gender

Age Group	White	Black	Latino/Hispanic	East Asian	Southeast Asian	Indian	Middle Eastern
0-2	0.66	0.68	0.84	0.76	0.56	0.61	1.00
3-9	0.73	0.69	0.70	0.83	0.84	0.72	0.72
10-19	0.74	0.68	0.87	0.84	0.83	0.75	0.82
20-29	0.92	0.83	0.93	0.92	0.90	0.95	0.95
30-39	0.92	0.87	0.96	0.89	0.89	0.93	0.95
40-49	0.93	0.87	0.93	0.85	0.89	0.94	0.95
50-59	0.90	0.79	0.95	0.90	0.84	0.90	0.94
60-69	0.84	0.81	0.91	0.80	0.77	0.82	0.95
70+	0.82	0.80	0.75	0.86	0.87	0.76	0.83

Table 4.2: Gender Prediction Accuracy Across Age and Ethnicity

Gender	White	Black	Latino/Hispanic	East Asian	Southeast Asian	Indian	Middle Eastern
Male	0.48	0.45	0.51	0.58	0.54	0.52	0.53
Female	0.51	0.43	0.49	0.59	0.50	0.48	0.55

Table 4.3: Age Prediction Accuracy Across Gender and Ethnicity

Gender	0-2	3-9	10-19	20-29	30-39	40-49	50-59	60-69	70+
Male	0.61	0.65	0.62	0.60	0.58	0.57	0.50	0.56	0.57
Female	0.55	0.58	0.64	0.59	0.59	0.58	0.60	0.61	0.60

Table 4.4: Ethnicity Prediction Accuracy Across Gender and Age

4.4. Observations

- The model often misclassifies age groups to adjacent categories (e.g., predicting `30-39` as `20-29`).
- Female subjects exhibit more misclassification in age prediction compared to males.
- Higher misclassification rates between similar ethnic groups (e.g. East Asian vs Southeast Asian).
- Consistent performance across genders, indicating balanced bias handling.
- Gender classification accuracy is highest in the 20-39 age groups across almost all ethnicities, indicating better performance for adults.
- Gender prediction accuracy for **Black** individuals is consistently lower compared to other groups across age categories.
- East Asian exhibit the highest age prediction accuracy for both genders among ethnicity groups.
- Black exhibit the lowest age prediction accuracy for both genders.
- Gender-based disparities are not very pronounced in all the groups.
- Age prediction accuracy values are below 60% across all gender-ethnicity combinations, highlighting the need for improved age prediction mechanisms.

4.5. Model Limitations

- Age Prediction: Low accuracy indicates the model's limited capability in distinguishing age groups, especially in extreme ranges.
- Ethnicity Overlap: High similarity between certain ethnic groups leads to increased misclassification rates.
- Despite balanced representation, some demographic subsets (e.g., certain age or ethnicity groups) still pose challenges.

5. Conclusion and Future Work

This project successfully developed and deployed a multitask CNN capable of predicting gender, age group, and ethnicity from facial images. Utilizing the FairFace dataset, the model demonstrated high accuracy in gender classification while highlighting areas for improvement in age and ethnicity predictions. The deployment via Streamlit showcased the model's practical applicability, bridging the gap between development and real-world use cases.

5.1. Improving Data Imbalance Handling

Despite FairFace's balanced representation, further enhancements in handling class imbalance are essential:

- **Advanced Resampling Techniques:** Implement Borderline-SMOTE or ADASYN to generate synthetic samples for underrepresented classes, thereby improving model training.
- **Class Weight Adjustment:** Adjust class weights dynamically during training to emphasize minority classes, reducing bias toward majority classes.
- **Cost-sensitive Learning:** Incorporate cost-sensitive frameworks where misclassification penalties are adjusted based on class distribution, enhancing model fairness.

5.1.1. Model Optimization and Hyperparameter Tuning

Future work could involve an extensive optimization process to improve the model's hyperparameters. Current methods like grid search and random search could be expanded by applying more sophisticated optimization techniques such as:

- **Bayesian Optimization:** Utilize Bayesian methods to explore the hyperparameter space more efficiently, identifying optimal configurations that enhance model performance.
- **Hyperparameter Importance Analysis:**Conduct systematic analyses to determine which hyperparameters significantly impact model accuracy, guiding more focused optimization efforts.

5.1.2. Exploring More Advanced Models

Future work could experiment with more advanced/complex models, particularly deep learning methods:

- **Generative Adversarial Networks (GANs):** Use GANs for data augmentation, particularly to generate synthetic images for underrepresented demographics, thereby enriching the training dataset.
- **Transfer Learning:** Fine-tune pre-trained models like ResNet or MobileNet on the FairFace dataset to leverage existing feature representations, potentially improving accuracy in age and ethnicity predictions.
- **ViT::** Experiment with transformer-based architectures to capture long-range dependencies in facial features, which may enhance classification performance.

5.1.3. Fairness and Bias Analysis

Addressing fairness and bias in machine learning models is essential, particularly when dealing with sensitive demographic factors. Future work should include:

- **Fairness Metrics:** Metrics such as demographic parity, equal opportunity, and disparate impact should be introduced to evaluate and mitigate bias in model predictions across different groups.
- **Bias Mitigation Techniques:** Techniques like adversarial debiasing, bias correction algorithms, and fairness constraints could be applied to ensure that the model performs equitably across different demographic groups.

5.1.4. Model Interpretability

- Explainable AI (XAI): Incorporate tools like SHAP and LIME to elucidate the model's decision-making process, providing transparency and facilitating the identification of potential biases.
- Attention Maps: Utilize Grad-CAM to visualize which facial regions the model prioritizes for its predictions, ensuring it focuses on relevant features.

5.1.5. Conclusion

While the current model excels in gender classification, significant improvements are needed for age and ethnicity predictions. Future work will focus on advanced data handling, model optimization, fairness enhancements, and expanded deployment strategies to create a more robust and equitable demographic prediction system.

6. Appendix

6.1. Model Implementation Code

```python
import torch
import torch.nn as nn
import torch.nn.functional as F

class DepthwiseSeparableConv(nn.Module):
    def __init__(self, in_channels, out_channels, stride=1):
        super(DepthwiseSeparableConv, self).__init__()
        self.depthwise = nn.Conv2d(in_channels, in_channels, kernel_size=3, stride=
            stride, padding=1, groups=in_channels, bias=False)
        self.pointwise = nn.Conv2d(in_channels, out_channels, kernel_size=1, bias=False
            )
        self.bn = nn.BatchNorm2d(out_channels)
        self.relu = nn.ReLU(inplace=True)

    def forward(self, x):
        x = self.depthwise(x)
        x = self.pointwise(x)
        x = self.bn(x)
        return self.relu(x)

class LightweightMTLNet224(nn.Module):
    def __init__(self, num_classes_gender=2, num_classes_age=9, num_classes_ethnicity
        =7):
        super(LightweightMTLNet224, self).__init__()

        # Input layer
        self.conv1 = DepthwiseSeparableConv(3, 64, stride=2)
        self.conv2 = DepthwiseSeparableConv(64, 128, stride=1)
        self.conv3 = DepthwiseSeparableConv(128, 128, stride=2)
        self.conv4 = DepthwiseSeparableConv(128, 256, stride=1)
        self.conv5 = DepthwiseSeparableConv(256, 256, stride=2)
        self.conv6 = DepthwiseSeparableConv(256, 512, stride=1)
        self.conv7 = DepthwiseSeparableConv(512, 512, stride=2)

        # Pooling layer
        self.avgpool = nn.AdaptiveAvgPool2d((1, 1))

        # Task-specific classifiers
        self.fc = nn.Linear(512, 256)
        self.gender_fc = nn.Linear(256, num_classes_gender)
        self.age_fc = nn.Linear(256, num_classes_age)
        self.ethnicity_fc = nn.Linear(256, num_classes_ethnicity)

```

```python
    def forward(self, x):
        # Pass through convolutional layers
        x = self.conv1(x)
        x = self.conv2(x)
        x = self.conv3(x)
        x = self.conv4(x)
        x = self.conv5(x)
        x = self.conv6(x)
        x = self.conv7(x)

        # Global average pooling
        x = self.avgpool(x)
        x = torch.flatten(x, 1)

        # Fully connected layers
        x = F.relu(self.fc(x), inplace=False)

        # Multi-task outputs
        gender = self.gender_fc(x)
        age = self.age_fc(x)
        ethnicity = self.ethnicity_fc(x)

        return gender, age, ethnicity
```

Listing 6.1: LightweightMTLNet224 Implementation

6.2. Model Training Code

```python
# Loss functions for each output
gender_criterion = nn.CrossEntropyLoss()
age_criterion = nn.CrossEntropyLoss()
ethnicity_criterion = nn.CrossEntropyLoss()

# Optimizer
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)

num_epochs = 10
losses = []
test_losses = []
losses_gender = []
losses_age = []
losses_ethnicity = []
test_losses_gender = []
test_losses_age = []
test_losses_ethnicity = []

for epoch in range(num_epochs):
    model.train()
    running_loss = 0.0
    running_loss_gender = 0.0
    running_loss_age = 0.0
    running_loss_ethnicity = 0.0

    batch_idx = 1
    for images, (gender_labels, age_labels, ethnicity_labels) in train_loader:
        images = images.to(device)
```

```
        gender_labels = gender_labels.to(device)
        age_labels = age_labels.to(device)
        ethnicity_labels = ethnicity_labels.to(device)

        optimizer.zero_grad()

        # Forward pass
        gender_output, age_output, ethnicity_output = model(images)

        # Compute individual losses and combine them
        gender_loss = gender_criterion(gender_output, gender_labels)
        age_loss = age_criterion(age_output, age_labels)
        ethnicity_loss = ethnicity_criterion(ethnicity_output, ethnicity_labels)

        total_loss = gender_loss + age_loss + ethnicity_loss
        total_loss.backward()
        optimizer.step()

        if batch_idx % 200 == 0:
            print('Train Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f} \tGender Loss: {:.6f} \tAge Loss: {:.6f}\tEthnicity Loss: {:.6f}'.format(
                epoch+1, batch_idx * len(gender_labels), len(train_dataset),
                100. * batch_idx / len(train_loader), total_loss.item(),
                gender_loss.item(), age_loss.item(), ethnicity_loss.item()))
        batch_idx += 1

        running_loss += total_loss.item()
        running_loss_gender += gender_loss.item()
        running_loss_age += age_loss.item()
        running_loss_ethnicity += ethnicity_loss.item()

    losses.append(running_loss/len(train_loader))
    losses_gender.append(running_loss_gender/len(train_loader))
    losses_age.append(running_loss_age/len(train_loader))
    losses_ethnicity.append(running_loss_ethnicity/len(train_loader))

    print(f"Epoch [{epoch+1}/{num_epochs}], Training Loss: {running_loss/len(train_loader):.4f}, Gender Loss: {running_loss_gender/len(train_loader):.4f}, Age Loss: {running_loss_age/len(train_loader):.4f}, Ethnicity Loss: {running_loss_ethnicity/len(train_loader):.4f}")

    running_loss = 0.0
    running_loss_gender = 0.0
    running_loss_age = 0.0
    running_loss_ethnicity = 0.0

    for images, (gender_labels, age_labels, ethnicity_labels) in val_loader:

        images = images.to(device)
        gender_labels = gender_labels.to(device)
        age_labels = age_labels.to(device)
        ethnicity_labels = ethnicity_labels.to(device)

        gender_output, age_output, ethnicity_output = model(images)

        # Compute individual losses and combine them
        gender_loss = gender_criterion(gender_output, gender_labels)
        age_loss = age_criterion(age_output, age_labels)
```

```
            ethnicity_loss = ethnicity_criterion(ethnicity_output, ethnicity_labels)

            total_loss = gender_loss + age_loss + ethnicity_loss

            running_loss += total_loss.item()
            running_loss_gender += gender_loss.item()
            running_loss_age += age_loss.item()
            running_loss_ethnicity += ethnicity_loss.item()

        test_losses.append(running_loss/len(val_loader))
        test_losses_gender.append(running_loss_gender/len(val_loader))
        test_losses_age.append(running_loss_age/len(val_loader))
        test_losses_ethnicity.append(running_loss_ethnicity/len(val_loader))
        print(f"Epoch [{epoch+1}/{num_epochs}], Test Loss: {running_loss/len(val_loader)
            :.4f}, Gender Loss: {running_loss_gender/len(val_loader):.4f}, Age Loss: {
            running_loss_age/len(val_loader):.4f}, Ethnicity Loss: {running_loss_ethnicity
            /len(val_loader):.4f}")

        evaluate(model, val_loader)

        # Stopping criteria
        if len(losses) > 1 and (losses[-1] > losses[-2] or losses[-2] - losses[-1] < 0.1):
            print("Early stopping triggered")
            break
```
Listing 6.2: LightweightMTLNet224 Training

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