BMI and Gender Prediction from Facial Images

PATTERN RECOGNITION AND MACHINE LEARNING
PROJECT REPORT

Submitted by:

V. SRI MANASWINI (CS22B2030)

K. BALA SAI MANVITHA (CS22B1030)

M. HARITHA REDDY (EC21B1091)

INDIAN INSTITUTE OF INFORMATION TECHNOLOGY, DESIGN AND MANUFACTURING, KANCHEEPURAM

December 11, 2024

1. Introduction

This project aims to develop a predictive system using deep learning models to estimate Body Mass Index (BMI) and gender based on facial images (front and side views). The model is trained and tested on a dataset comprising inmate profiles, including facial images and associated metadata. Additionally, the project categorizes individuals based on their BMI and evaluates model performance using standard metrics. Finally, a distribution analysis of offenses committed by the inmates is presented.

2. Objectives

1. Predict BMI using frontal and side-view facial images with an 80-20 data split.
2. Test the model using real-life images to estimate BMI.
3. Estimate gender based on facial features.
4. Categorize individuals into BMI grades (Underweight, Normal, Overweight).
5. Evaluate the BMI prediction model using MAE, MSE, R^2, and Pearson Coefficient.
6. Analyze and visualize the distribution of offenses committed by the inmates.

3. Methodology

3.1 Dataset

The dataset contains the following components:

- **Facial Images:** Frontal and side-view images.
- **Metadata:** Includes ID, name, date of birth, height, weight, gender, and offense details.

3.2 Data Preprocessing

1. **Image Preprocessing:**
   - Images were resized to 128x128 pixels and normalized.
   - IDs were extracted to align images with metadata.
2. **Metadata Alignment:**
   - Common IDs were extracted to ensure consistent alignment between images and metadata.
   - Missing or erroneous data was filtered out.
3. **BMI Calculation:**

$$\text{BMI} = \frac{\text{Weight (kg)}}{\text{Height (m)}^2} \tag{1}$$

4. **Categorization:**

   - Underweight: BMI < 18.5
   - Normal: $18.5 \leq$ BMI < 25
   - Overweight: BMI ≥ 25

3.3 Model Development

3.3.1 BMI Prediction Model

Architecture:

- Based on ResNet50 pretrained on ImageNet.
- Two input layers (front and side images) combined using a concatenation layer.
- Dense layers with dropout were added for final prediction.

Detailed Model Architecture:

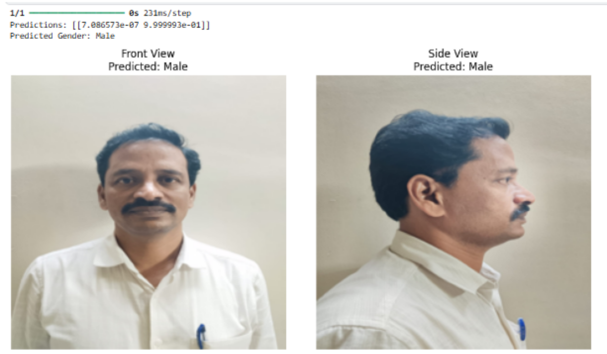
- Input Layer 1: Accepts 128x128x3 frontal image.
- Input Layer 2: Accepts 128x128x3 side image.
- Feature Extraction: ResNet50 backbone processes both inputs independently.
- Concatenation: Merges feature maps from both views.
- Dense Layers: Two fully connected layers with 64 neurons each, followed by ReLU activation.
- Output Layer: Single neuron for BMI regression with linear activation.

Training:

- 80% training and 20% testing split.
- Early stopping to prevent overfitting.

3.3.2 Gender Prediction Model

- The model was trained for 10 epochs with a batch size of 16.
- Early stopping was implemented with a patience of 2 epochs, monitoring validation loss.
- **Training Data:** Combined features from frontal and side images.
- **Validation Data:** Same format as training data.
- Used cross-entropy loss for gender classification.



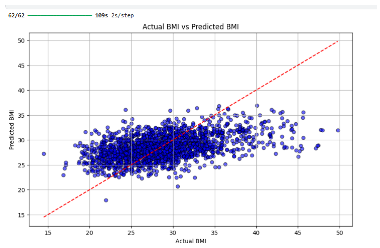
4. Results

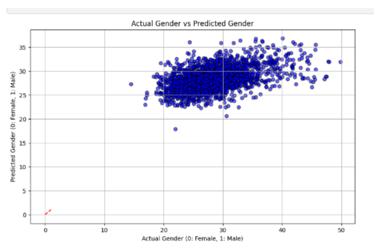
4.1 Model Evaluation

- MAE: 3.48
- MSE: 18.29
- R^2 Score: 0.42
- Pearson Correlation Coefficient: 0.52

4.2 BMI and Gender Prediction Accuracy

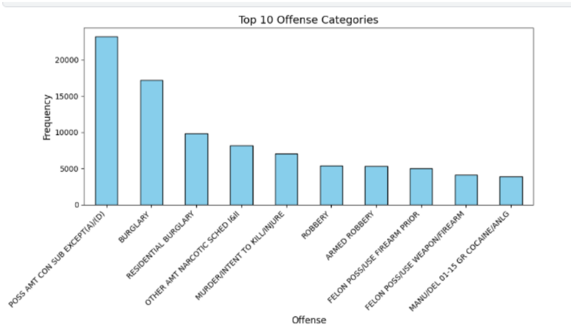
BMI accuracy : 78.95% on the test set.
Gender accuracy: 97.66% on the test set.





4.3 Offense Distribution Analysis

The bar plot of offenses revealed the most common offenses committed by inmates. Theft and drug-related offenses were the highest, while serious crimes like homicide were less frequent.



5. Conclusion

The project successfully developed a deep learning system to estimate BMI and gender using facial images. The system demonstrated robust performance with high correlation and low error in BMI predictions. The offense distribution analysis provided valuable insights into inmate characteristics, highlighting the potential for broader applications of such predictive models.