PRML PROJECT

BMI and Gender Prediction from Facial Images

K BALA SAI MANVITHA
V SRI MANASWINI
M HARITHA REDDY

Overview

Objectives

- Predict BMI and gender from facial features using computational models
- Leverage deep learning for accurate predictions using ResNet50.

Challenges

- Non-linear relationships between facial features and BMI.
- Variation in facial structure due to age, lighting, ethnicity.

Goals

- Accurate BMI prediction.
- Robust gender classification
- Offense distribution

Preprocessing

1. **Image Preprocessing:**
    - Resized images to 128×128 pixels and normalized pixel values to 0–1.
    - Processed both frontal and side view images for dual input.
2. **Metadata Alignment:**
    - Aligned metadata and images using unique IDs.
    - Filtered out mismatches to ensure consistency.
3. **Corrupted Data Handling:**
    - Skipped and logged corrupted or unreadable image files.
    - Ensured data quality by maintaining only valid entries.

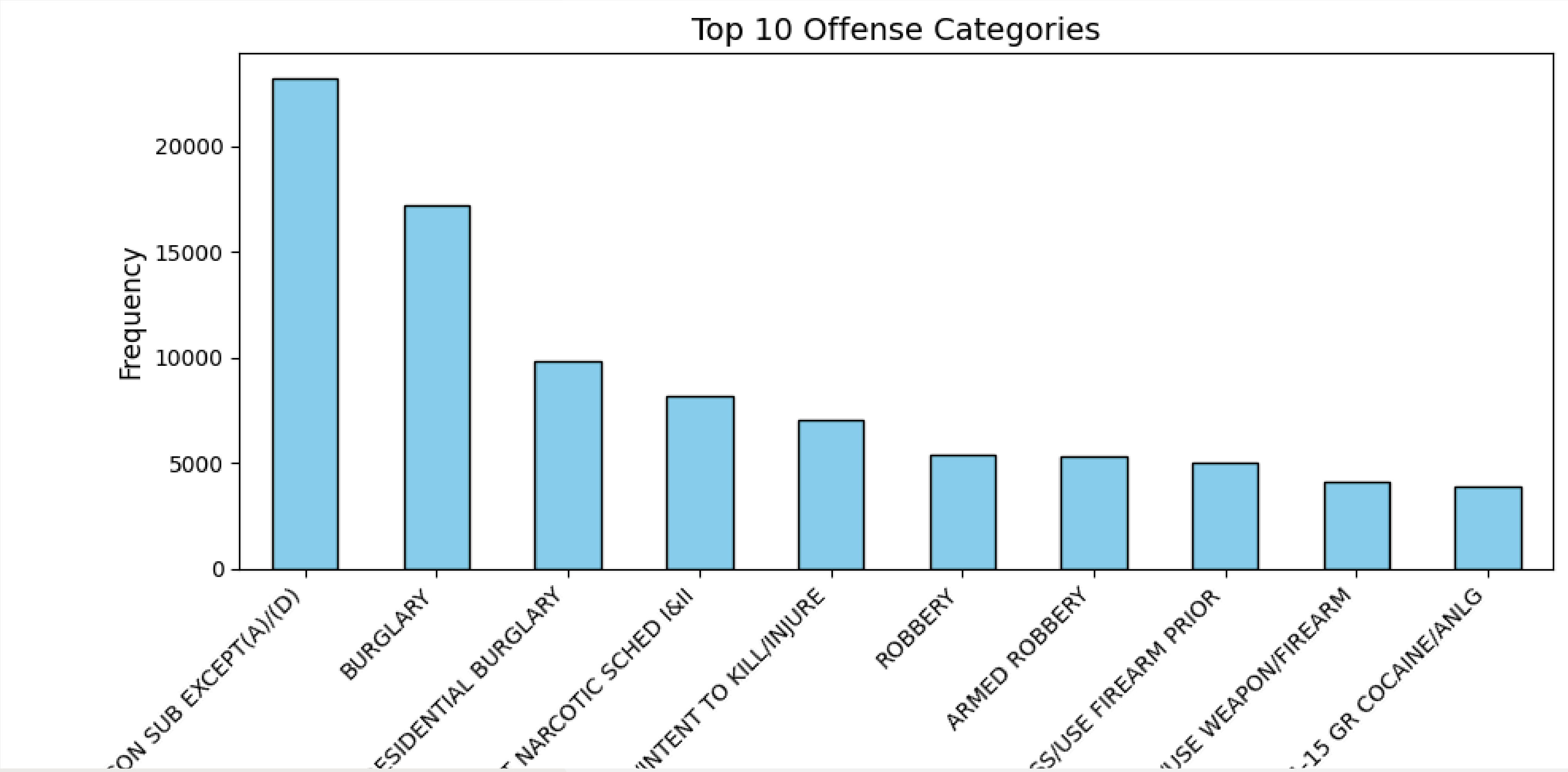
BMI Categorization

Categories:

- Underweight: $BMI < 18.5$
- Normal: $18.5 \le BMI < 25$
- Overweight: $BMI \ge 25$

Offense Distribution

The top 10 offense categories were visualized using a bar chart, highlighting the most frequent offenses among inmates.



Model Architecture

BMI Prediction Model:

- Utilized dual ResNet50 extractors for frontal and side view images.
- Combined features from both perspectives using concatenation.
- Dense and Dropout layers used to refine feature representation.
- Final layer predicts BMI as a continuous value with linear activation.
- Architecture enhances prediction accuracy by leveraging complementary views.
- Layers: Dense (64), Dropout (0.3), Output (1 neuron, linear activation).

Model Architecture

Gender Classification Model:

- Single ResNet50 feature extractor used for frontal images.
- Dense layers process extracted features for classification.
- Output layer with sigmoid activation for binary classification (Male/Female).
- Binary Cross-Entropy used as the loss function.
- Optimized with Adam and evaluated using Accuracy metric.
- Layers: Dense (64), Dropout (0.3), Output (softmax for gender categories).

Training and Testing

BMI Prediction Model:

a. Loss Function: The model was trained to minimize the Mean Squared Error (MSE), penalizing large deviations in BMI predictions.
b. Metrics: MAE, R^2 Score, Pearson Correlation.

Gender Prediction Model:

a. Loss Function: Binary Cross-Entropy to handle binary classification.
b. Metrics: Accuracy to evaluate classification performance

- Optimizer: The Adam Optimizer was used for efficient parameter updates.
- Dataset Split: 80% training, 20% testing.
- Strategy: 5 epochs, batch size 16, with Early Stopping to prevent overfitting

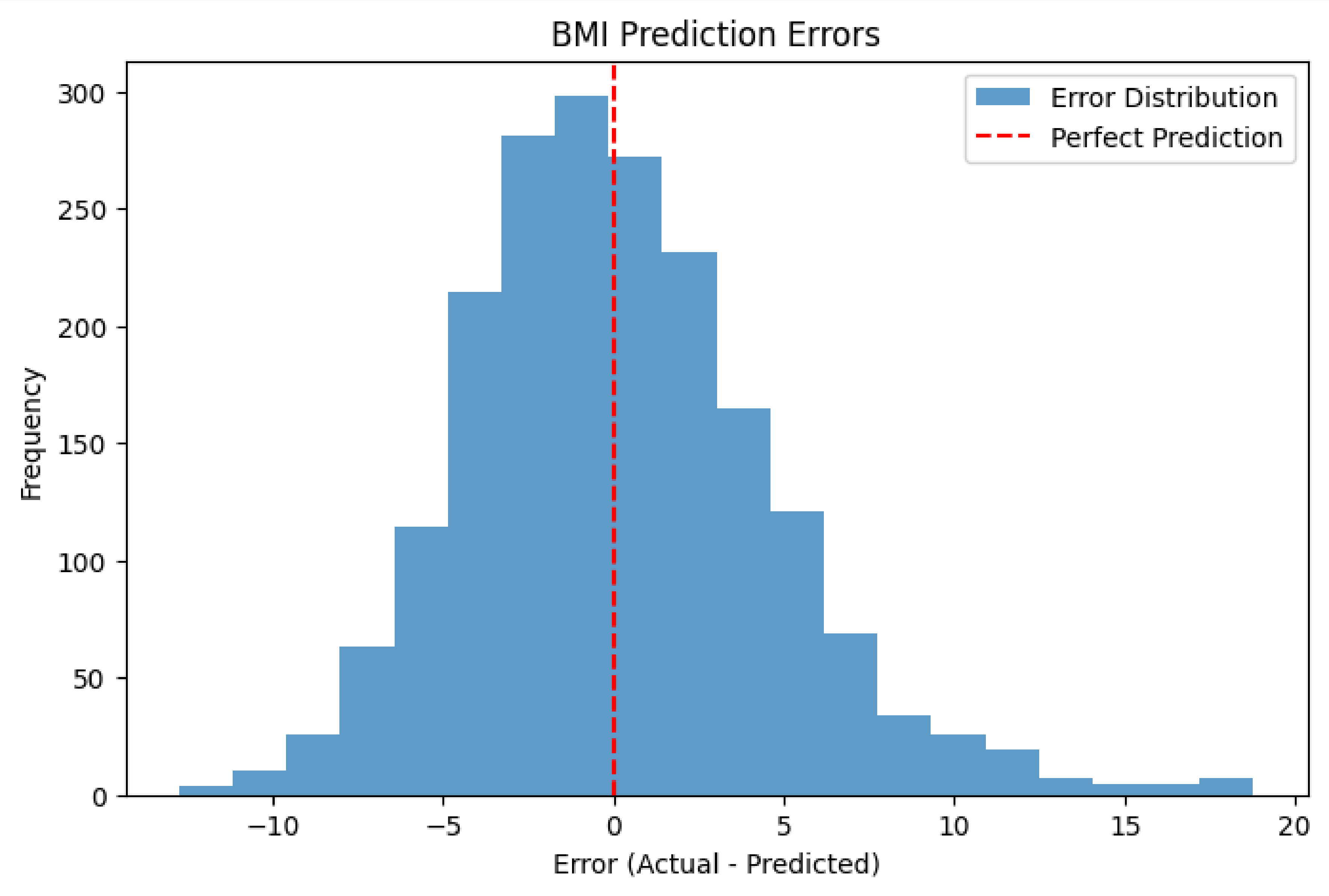
Results

BMI Prediction

- Metrics:
  - Mean Absolute Error (MAE): 3.48
  - Mean Squared Error (MSE): 18.29
  - R2 Score: 0.42
  - Pearson Correlation Coefficient: 0.52
- BMI Accuracy: 78.95%

Gender Prediction

- Metrics:
  - Accuracy: 98%
  - Confusion Matrix (Image).



	precision	recall	f1-score	support
0	1.00	0.00	0.00	46
1	0.98	1.00	0.99	1925
accuracy			0.98	1971
macro avg	0.99	0.50	0.49	1971
weighted avg	0.98	0.98	0.97	1971

Conclusion

- Successfully implemented a multi-input deep learning model.
- Predicted BMI with reasonable accuracy and gender with high precision.
- Plotted top 10 offence distribution

Thank you