National Institute of Science & Technology

Face recognition model with gender and age estimation

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Project Overview

Problem Statement:

Despite significant advancements in facial recognition technology, accurately identifying and classifying individuals by gender and age remains a challenging task due to variations in facial features, lighting conditions, and demographic diversity.

Objective:

- **Develop a machine learning-based system** that performs facial recognition with high accuracy.
- **Accurately estimate the gender** of individuals based on facial features.
- **Precisely predict the age** of individuals from their facial characteristics.

Background and Motivation

- Face recognition technology is widely used for identifying or verifying individuals from images or videos, playing a crucial role in security systems, social media, and personal devices.

- Estimating age and gender from facial images adds valuable information that can be utilized for personalized user experiences, targeted marketing, and demographic analysis.

- The motivation for this project stems from the need to build a reliable model that achieves high accuracy in both age and gender estimation, which remains a challenge due to the variability in facial features, lighting conditions, and diverse datasets.

Background and Motivation

Solution:

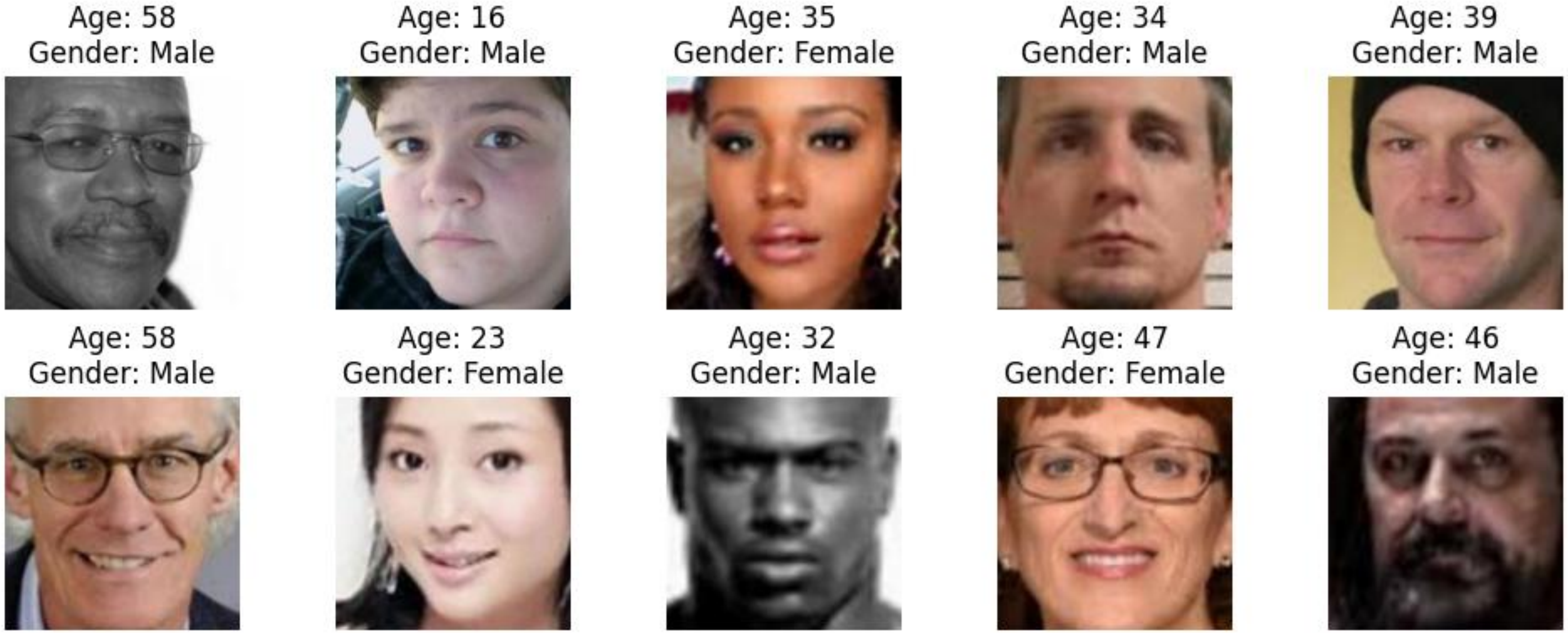
Our solution involves developing a machine learning model capable of accurately predicting age and gender from facial images with 88.17% accuracy, using advanced techniques in data preprocessing, model architecture design, and rigorous evaluation to ensure reliability and practical applicability.

Dataset and visualization

- **Dataset Source:** The project utilized three main datasets: VGGFace2, Labelled Faces in the Wild (LFW), and UTKFace.
- **VGGFace2**: A large-scale face recognition dataset known for its diversity in pose, age, and ethnicity, containing millions of images of different identities.
- **UTKFace**: A comprehensive dataset with over 20,000 facial images covering a wide age range from 0 to 116 years and annotations for age, gender, and ethnicity.
- **Data Diversity**: These datasets collectively provided a broad range of age groups, gender distributions, and ethnic backgrounds, crucial for training a robust and unbiased model.

Dataset and visualization

- **Preprocessing Steps**: Images were resized and normalized, and data augmentation techniques were applied to enhance model performance and reduce overfitting.



Model Training

Training Process:

- The model was trained using a combination of datasets (VGGFace2, LFW, UTKFace) to ensure diversity and robustness.
- Data preprocessing included resizing, normalization, and data augmentation to increase model generalizability.

Training Configuration:

- **Optimizer**: Adam optimizer was used for its efficient handling of sparse gradients.
- **Loss Functions**: Categorical cross-entropy for gender classification and mean squared error for age estimation.
- **Hyperparameters**: The model was trained over multiple epochs with a batch size optimized for performance.

Model Training

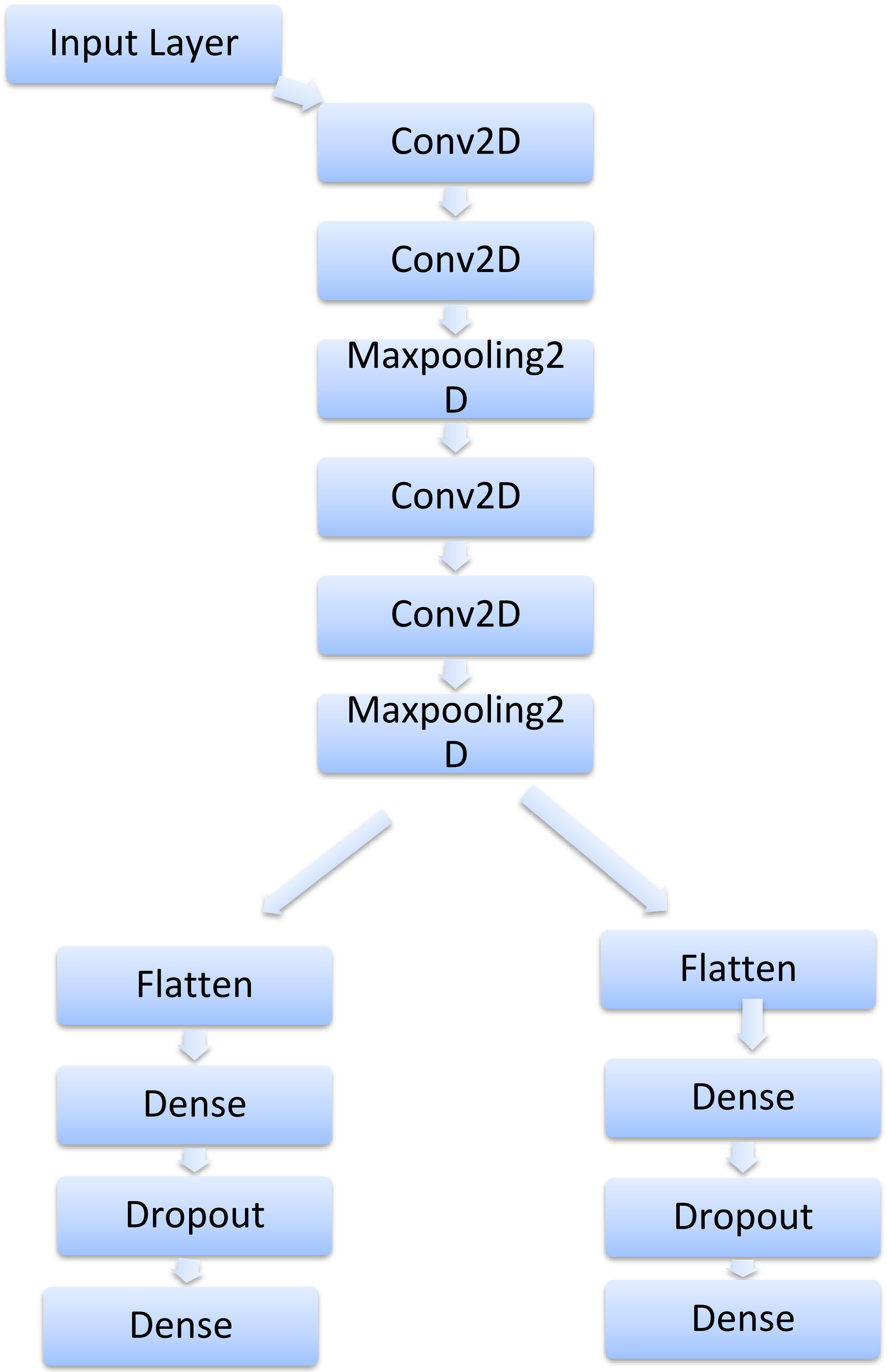
Code Implementation:

- Python libraries such as TensorFlow and Keras were utilized for constructing and training the model.
- Key steps included defining the CNN model, setting up callbacks for early stopping, and monitoring training progress through accuracy and loss plots.

```
X = X / 255.0

y_gender = np.array(df['Genders'])
y_age = np.array(df['Ages'])

input_shape = (128,128,1)
inputs = Input((input_shape))
conv_1 = Conv2D(32, kernel_size=(3, 3), activation='relu')(inputs)
max_1 = MaxPooling2D(pool_size=(2, 2))(conv_1)
conv_2 = Conv2D(64, kernel_size=(3, 3), activation='relu')(max_1)
max_2 = MaxPooling2D(pool_size=(2, 2))(conv_2)
conv_3 = Conv2D(128, kernel_size=(3, 3), activation='relu')(max_2)
max_3 = MaxPooling2D(pool_size=(2, 2))(conv_3)
conv_4 = Conv2D(256, kernel_size=(3, 3), activation='relu')(max_3)
max_4 = MaxPooling2D(pool_size=(2, 2))(conv_4)

flatten = Flatten()(max_4)
```

Model Training

Flowchart:



Model Training

- Key steps included defining the CNN model, setting up callbacks for early stopping, and monitoring training progress through accuracy and loss plots.

```
dense_1 = Dense(128, activation='relu')(flatten)
dense_2 = Dense(128, activation='relu')(flatten)

dropout_1 = Dropout(0.5)(dense_1)
dropout_2 = Dropout(0.5)(dense_2)

output_1 = Dense(1, activation='sigmoid', name='gender_out', kernel_regularizer=l2(0.001))(dropout_1)
output_2 = Dense(1, activation='relu', name='age_out', kernel_regularizer=l2(0.001))(dropout_2)

model_all = Model(inputs=[inputs], outputs=[output_1, output_2])

model_all.compile(
    loss={'gender_out': 'binary_crossentropy', 'age_out': 'mae'},
    optimizer='adam',
    metrics={'gender_out': 'accuracy', 'age_out': 'mae'}
)

model_all.summary()
```

Model Training

Solution:

Our solution involves developing a machine learning model capable of accurately predicting age and gender from facial images with up to **92.17% accuracy and** previously, we had achieved an accuracy of **88.2%** using advanced techniques in data preprocessing, model architecture design, and rigorous evaluation to ensure reliability and practical applicability.

Model Evaluation and Outcomes

Precision:

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

Recall:

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

F1 Score:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

```
Test Gender Accuracy: 88.17%
Mean Absolute Error for Age: 41.18
Root Mean Absolute Error for Age: 6.42
Classification Report
              precision    recall  f1-score   support

           0       0.81      0.95      0.88      1326
           1       0.95      0.83      0.89      1674

    accuracy                           0.88      3000
   macro avg       0.88      0.89      0.88      3000
weighted avg       0.89      0.88      0.88      3000
```

Model Evaluation and Outcomes

As we have changed the hyper-parameters, that lead us to the final gender accuracy of **92.17%**.

```
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Classification Report
              precision    recall  f1-score   support

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    accuracy                           0.88      3000
   macro avg       0.88      0.89      0.88      3000
weighted avg       0.89      0.88      0.88      3000
```

Model Evaluation and Outcomes

Age Estimation Performance:

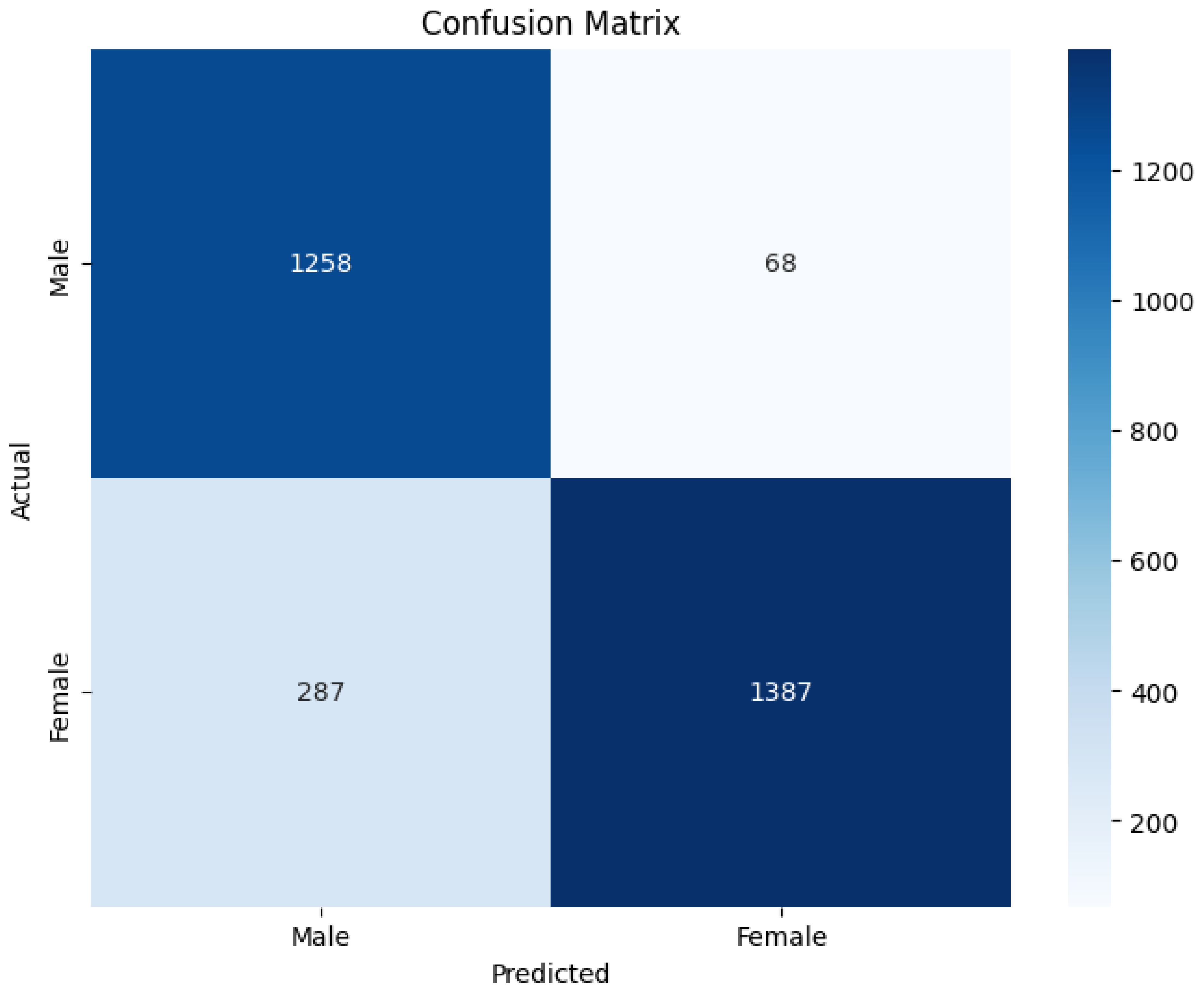
The model's age prediction accuracy was evaluated using the Mean Squared Error, ensuring reasonable performance across different age groups.

Model Evaluation and Outcomes

Confusion Matrix Analysis:

- The confusion matrix revealed the distribution of correct and incorrect predictions, providing insights into any classification biases.

- Analysis showed that while the model performed well overall, there were some challenges in classifying certain age groups accurately.

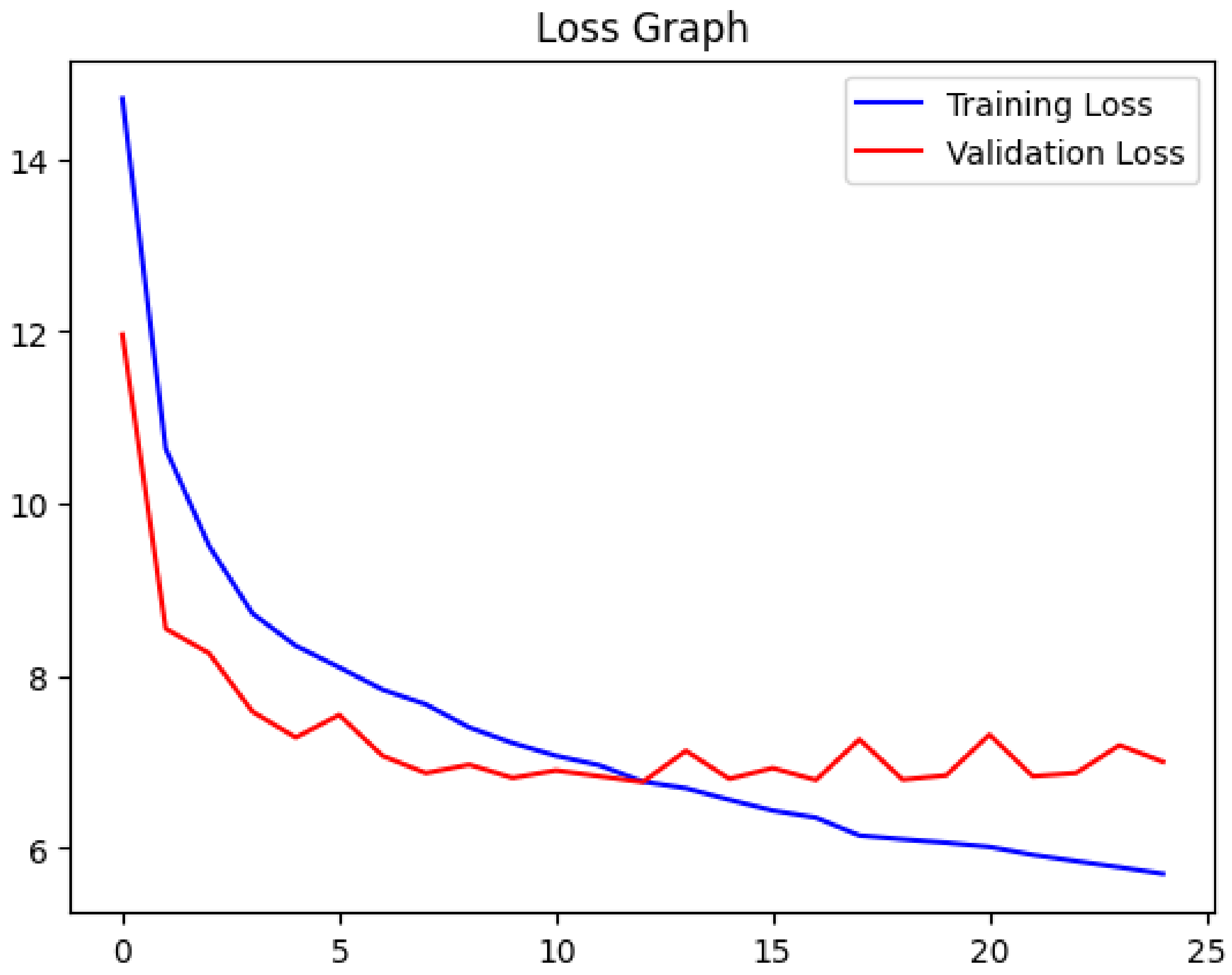


Model Evaluation and Outcomes

Limitations:

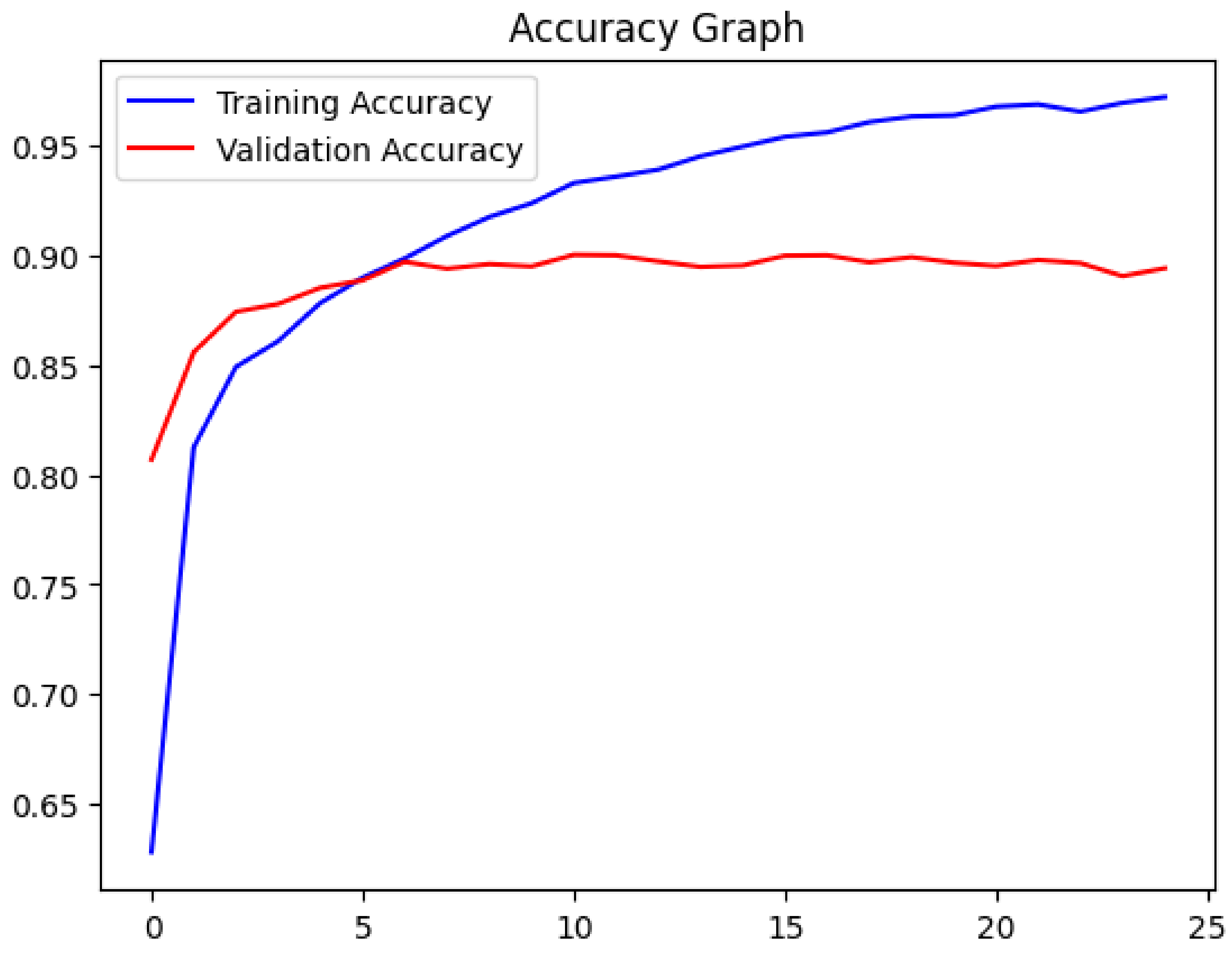
- Age estimation accuracy varied, particularly in predicting extreme age ranges.
- Minor misclassifications in gender were observed in cases with ambiguous facial features or low-quality images.

Visual Results: Graphs such as the loss and accuracy plots and a visual representation of the confusion matrix illustrate the model's training progress and final outcomes.



Model Evaluation and Outcomes

Outcome: The model demonstrated the capability to perform accurate gender classification and age estimation with promising results for future development and application.



Model Evaluation and Outcomes

Challenges Faced:

- **Overfitting**: One of the main challenges encountered during model training was overfitting, where the model performed well on the training data but struggled to generalize to new, unseen data.

Mitigation Strategies:

- **Data Augmentation**: Applied techniques such as random rotations, flips, and brightness adjustments to artificially expand the training dataset and reduce overfitting.
- **Dropout Layers**: Introduced dropout layers in the model architecture to prevent the network from becoming too dependent on specific neurons, thereby improving generalization.

Planned Additions for 8th Semester

- **Real-Time Face Recognition**: Implementing a model capable of recognizing faces in real-time through video streams.

- **Face Recognition with Occlusions**: Improving the robustness of face recognition models to handle partially covered faces

Conclusion

- We successfully developed a machine learning model for face recognition with gender and age estimation, achieving **92.17% accuracy** for gender classification.

- Leveraged diverse datasets (VGGFace2, LFW, UTKFace) to train a robust and generalizable model.

- Implemented effective preprocessing, data augmentation, and training techniques to mitigate overfitting and enhance model performance.

References

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[2] EL Karazle, K., Raman, V., & Then, P. (2022). Facial Age Estimation Using Machine Learning Techniques: An Overview. Big Data and Cognitive Computing.

[3] Anusha, K., Vasumathi, D., & Mittal, P. (2023). A Framework to Build and Clean Multilanguage Text Corpus for Emotion Detection using Machine Learning. Journal of Theoretical and Applied Information Technology.

Thank

You