



MENTORNESS

FACE AGING DETECTION USING DEEP LEARNING

PRESENTED BY: MD. SHAKIB

ABOUT PROJECT

- This project focuses on developing a deep learning model capable of predicting a person's age based on facial images.
- The goal is to create a system that can accurately analyze and classify images from a dataset to determine these demographic attributes.

TECHNOLOGIES USED:

- Python
- TensorFlow/Keras
- Google Colab
- Pandas and NumPy for data handling and preprocessing.





DATASET

The UTKFace Dataset is a large-scale face dataset that includes images with diverse variations in age, gender, and ethnicity. The dataset contains over 20,000 images of human faces, each labeled with the corresponding age, gender, and ethnicity information. The images cover a wide range of ages, from newborns to 116 years old, making it suitable for tasks related to age prediction.

OVERVIEW OF THE DATASET:

- **Number of Images:** Over 20,000 images.
- **Labels:** Age, Gender, and Ethnicity.
- **Type of Images:** Real-world face images with variations in pose, lighting, and expression.

MODEL ARCHITECTURE

- **Input Layer:**
- **Shape: 128x128x1** (Grayscale images with dimensions 128x128 pixels)
- **Convolutional Layers:**
- **Conv2D Layer 1:**
- **Filters: 32**
- **Kernel Size: 3x3**
- **Activation: ReLU**
- **Purpose: Detects low-level features such as edges and textures.**
- **MaxPooling2D Layer 1:**
- **Pool Size: 2x2**
- **Purpose: Reduces the spatial dimensions by downsampling, which helps in reducing the computational load and captures essential features.**
- **The model developed for age prediction is a Convolutional Neural Network (CNN) designed to handle the complexity of facial recognition tasks while being efficient enough to train on a large dataset like UTKFace.**

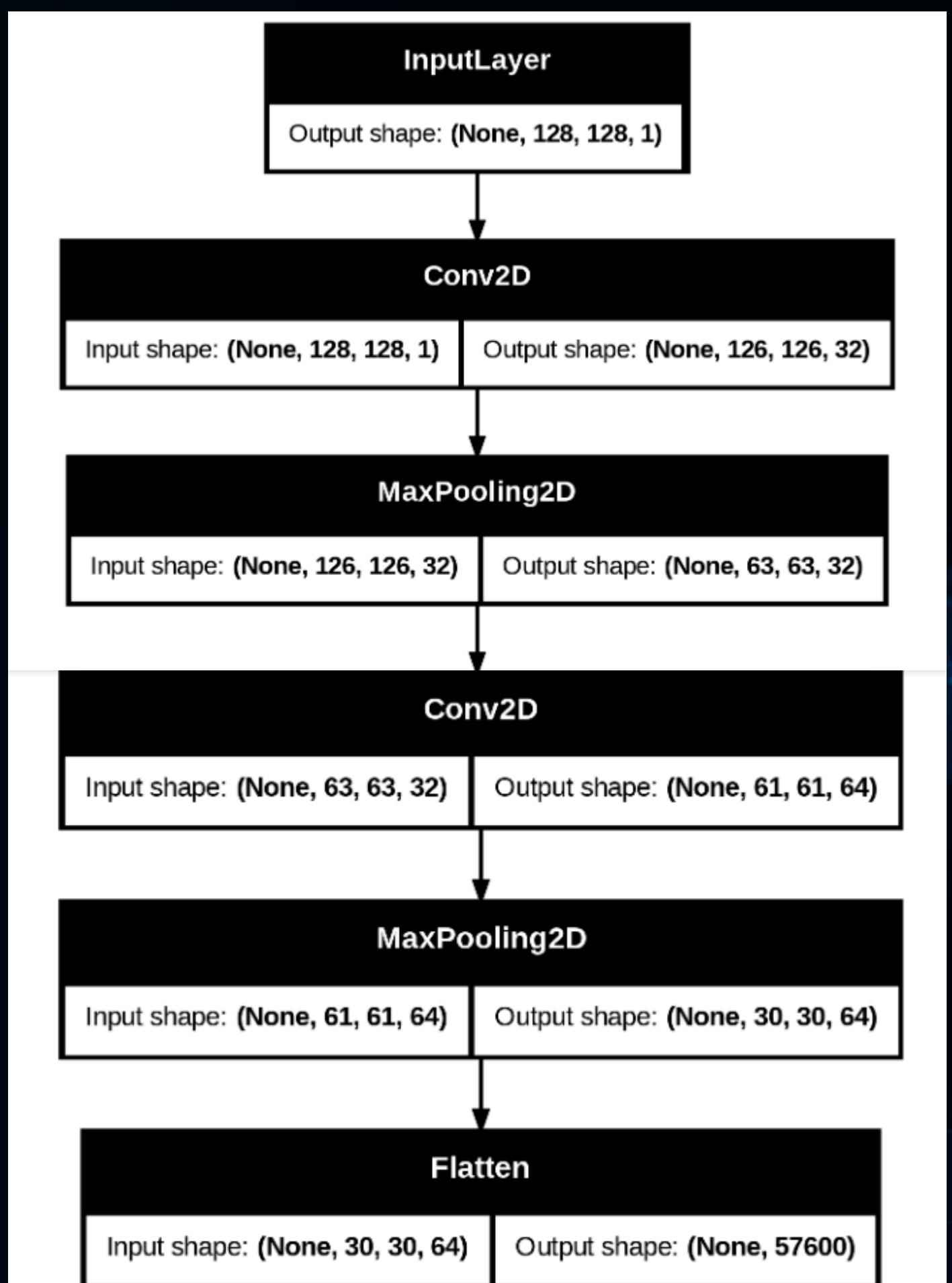
MODEL ARCHITECTURE

- Conv2D Layer 2:
 - Filters: 64
 - Kernel Size: 3x3
 - Activation: ReLU
 - Purpose: Extracts more complex features from the images.
- MaxPooling2D Layer 2:
 - Pool Size: 2x2
 - Purpose: Further downsampling to focus on the most prominent features.
- Flatten Layer:
 - Converts the 2D matrix output from the convolutional layers into a 1D vector, preparing it for the fully connected layers.
- Dense Layers:
 - Dense Layer 1:
 - Units: 128
 - Age Output:
 - Units: 1
 - Activation: Linear
 - Purpose: Predicts the age of the person in the image.

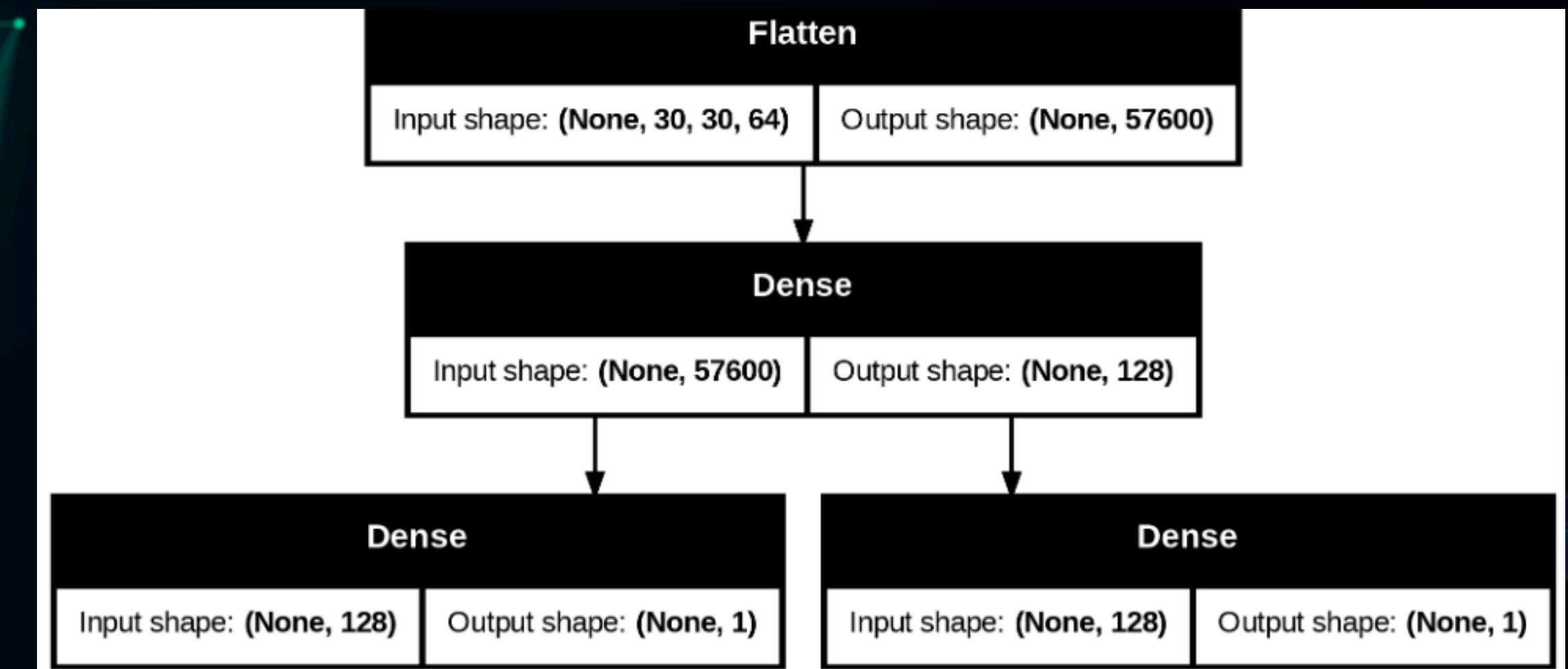
MODEL TRAINING



The model was designed with a focus on achieving accurate predictions for age using a relatively simple yet effective CNN architecture. The model summary provides a clear overview of the layers, their output shapes, and the total number of parameters, demonstrating the complexity and depth of the network.



MODEL TRAINING



- **Total Parameters:** The model has approximately hundreds of thousands of parameters, highlighting the complexity of the network and its capacity to learn from the data.
- **Loss Function:** Explain the loss function used during training (e.g., cross-entropy for classification tasks, mean squared error for regression).

TRAINING PROCESS

- **Epochs:** The model was trained for 50 epochs. However, early stopping was employed to prevent overfitting, which means training could have halted earlier based on validation loss.
- **Batch Size:** A batch size of 32 was used, balancing between computational efficiency and gradient estimation accuracy.

Epoch 1/50	593/593	532s	896ms/step	- age_mae: 15.4751
Epoch 2/50	593/593	515s	816ms/step	- age_mae: 15.4403
Epoch 3/50	593/593	493s	801ms/step	- age_mae: 13.2916
Epoch 4/50	593/593	504s	806ms/step	- age_mae: 11.5424
Epoch 5/50	593/593	477s	805ms/step	- age_mae: 11.1529
Epoch 6/50	593/593	483s	814ms/step	- age_mae: 10.5919
Epoch 7/50	593/593	496s	804ms/step	- age_mae: 10.4264
Epoch 8/50	593/593	503s	806ms/step	- age_mae: 10.1650
Epoch 9/50	593/593	478s	807ms/step	- age_mae: 10.0095
Epoch 10/50	593/593	501s	806ms/step	- age_mae: 9.7070
Epoch 11/50	593/593	478s	807ms/step	- age_mae: 9.6617
Epoch 12/50	593/593	479s	808ms/step	- age_mae: 9.3326
Epoch 13/50	593/593	511s	823ms/step	- age_mae: 9.1465

MODEL PERFORMANCE

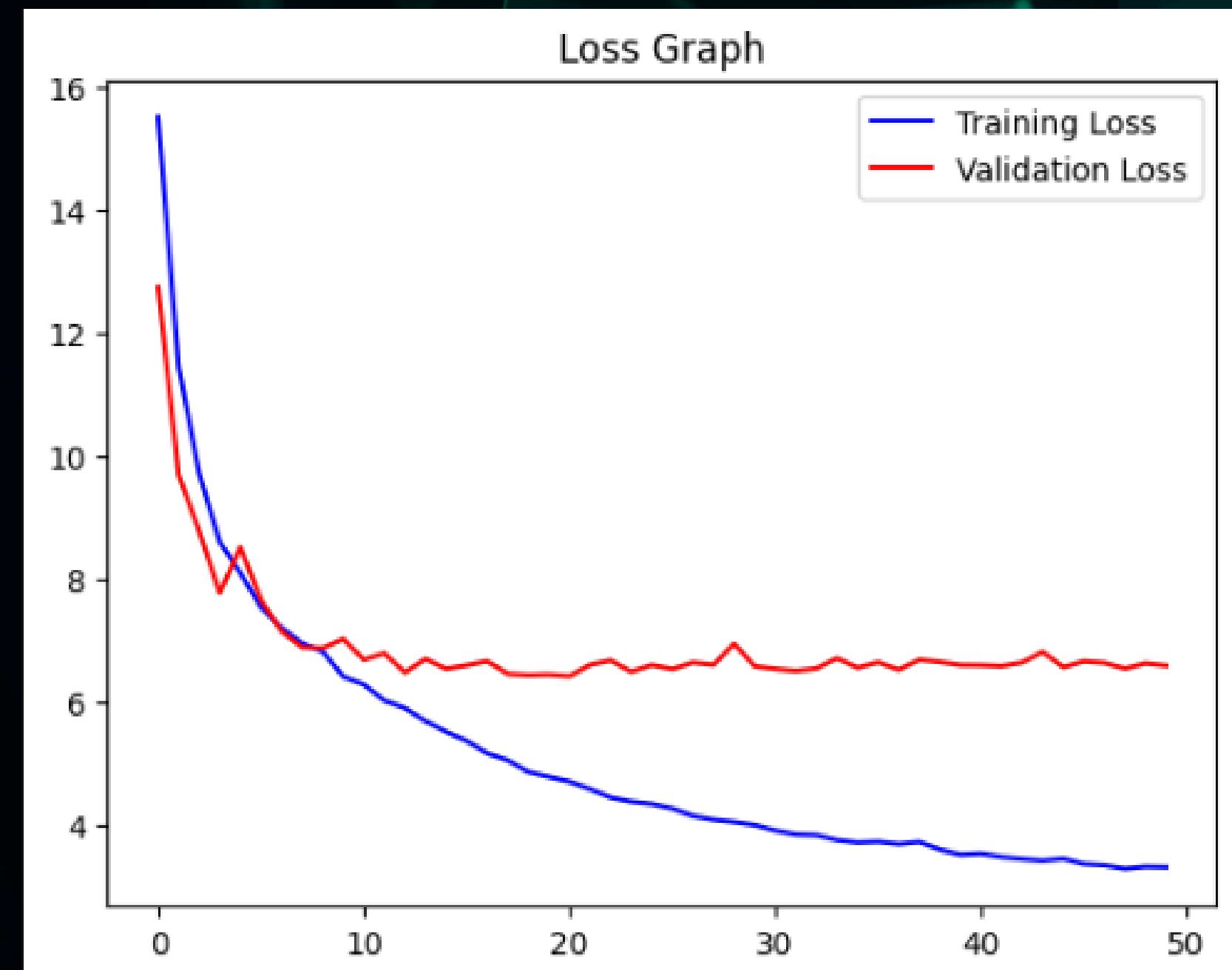
The model's performance during training was monitored using both the training loss and validation loss for age predictions.

TRAINING LOSS

The loss steadily decreased over epochs, indicating that the model was learning from the data.

VALIDATION LOSS

The validation loss also decreased initially, but plateaued as the model began to converge, indicating that early stopping was effective in preventing overfitting.



SAMPLE PREDICTION

These results will illustrate how well the model generalizes to new, unseen data and its potential applications in various fields, such as social media, security, and personalized marketing.

Predicted Age: 33 Predicted Gender: Female



FUTURE WORK



Enhanced Models: Consider using more complex architectures, such as deeper CNNs or ResNet, to improve feature extraction and prediction accuracy.

Data Augmentation: Apply advanced data augmentation techniques to simulate various real-world conditions and enhance model performance.

Real-time Prediction: Develop a real-time application or API to provide predictions on user-uploaded images dynamically.

Security: Use age predictions in security systems to enhance facial recognition technologies.

CONCLUSION



Developed a deep learning model to predict age and gender from facial images using the UTKFace dataset. Successfully built and trained a model with significant accuracy, showcasing predictions through sample images. Addressed challenges related to data preprocessing, model convergence, and achieved improvements through early stopping and efficient training.

THANK YOU!

FOR JOINING ME ON THIS JOURNEY OF EXPLORING FACE AGING DETECTION.
OUR KNOWLEDGE AND SKILLS WILL CONTINUE TO EVOLVE WITH PRACTICE AND EXPERIMENTATION.

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<https://www.linkedin.com/in/md-shakib-6283a7239/>



<https://github.com/shaky1405>