**Introduction**

The objective of this project was to develop a robust face emotion detection system using a state-of-the-art deep learning approach. Facial emotions play a crucial role in understanding human behavior, and automatic emotion detection has applications in areas such as mental health, human-computer interaction, and surveillance. This project employs YOLOv8, a high-performing object detection model, to identify and classify various facial emotions in real time or from static images. The project addresses the need for accurate and efficient emotion detection, which can benefit industries ranging from healthcare to entertainment.

**Method (Approach)**

The YOLOv8 model was selected for its speed, accuracy, and ability to handle object detection tasks effectively. The model was fine-tuned on a labeled facial emotion dataset to classify emotions such as happiness, sadness, anger, surprise, fear, disgust, and neutrality. Training involved applying augmentation techniques like flipping, rotation, and brightness adjustments to improve generalization. We trained the model using the Adam optimizer, with a learning rate of 0.002, batch size of 32, and for 80 epochs. The YOLOv8 framework allowed for real-time detection using its anchor-free architecture and lightweight design.

**Dataset**

The dataset used for this project was sourced from Roboflow and contains labeled facial images across multiple emotion classes. It includes 4,753 images annotated in YOLO format, making it compatible with the YOLOv8 framework. The dataset was pre-processed and split into training (80%), validation (10%), and testing (10%) subsets. Key data augmentation methods such as flipping, rotation, and brightness variations were applied to diversify the dataset. The images were resized to 640x640 resolution for consistency and improved model performance.

**Experiments**

Several experiments were conducted to test and refine the performance of YOLOv8 for facial emotion detection:

1. **Baseline Training**: The model was trained using the raw dataset without augmentation to establish baseline metrics.
2. **Augmented Training**: Augmented data improved the model’s ability to generalize across unseen images, enhancing accuracy.
3. **Evaluation Metrics**: Metrics like mean Average Precision (mAP), precision, recall, and F1 score were calculated. The model achieved an mAP of 94% on the test set.
4. **Real-Time Testing**: The trained model was integrated with a webcam for real-time detection, and performance was evaluated based on accuracy and inference speed.
5. **Implementation**
6. The project was implemented using Python and the ultralytics YOLOv8 library. The Roboflow API was used to manage the dataset. Model training and evaluation were carried out on a machine with an NVIDIA RTX 3080 GPU to ensure fast computation. The model’s output was visualized with bounding boxes and emotion labels for each detected face. A CustomTkinter-based GUI was developed to provide a user-friendly interface for uploading images and performing real-time emotion detection using a webcam.