Group - 9

STUDENT CONCENTRATION ANALYZER

INTRODUCTION

- Emotion recognition is pivotal in identifying and understanding human emotions through facial expressions, voice tone, and body language. Within the realm of computer vision and affective computing, facial emotion recognition plays a crucial role.
- The Student Concentration Analyzer aims to interpret the concentration levels and emotional states of learners by analyzing their facial cues during live online classes.

PROBLEM STATEMENT

- Online education struggles to maintain student engagement and accurately assess learner focus. The rapid evolution of this field necessitates sophisticated tools that can dynamically respond to students' emotional and attentional states to foster a more effective learning environment.

PROJECT FOCUS

- Utilizing the FER dataset and CNNs, this project develops a system to detect and analyze students' emotions in real-time. It addresses the need for improved interaction in virtual classrooms by enabling a responsive and adaptive educational experience.

Applications

- Educational Enhancement
- Personalized Learning
- Engagement Metrics
- Emotional Intelligence Development
- Accessibility Enhancements

These applications demonstrate the versatility of the Student Concentration Analyzer in enhancing the educational landscape and supporting diverse learning needs.

DATASET

- Introduction of FER+ dataset for analyzing learner’s facial emotion in LIVE environment.
- Total of 65520 images in the dataset.
- Preprocessing techniques including resizing to 48x48 pixels and converting to gray scaling for efficiency.

Emotion Class Distribution in FER+ Dataset

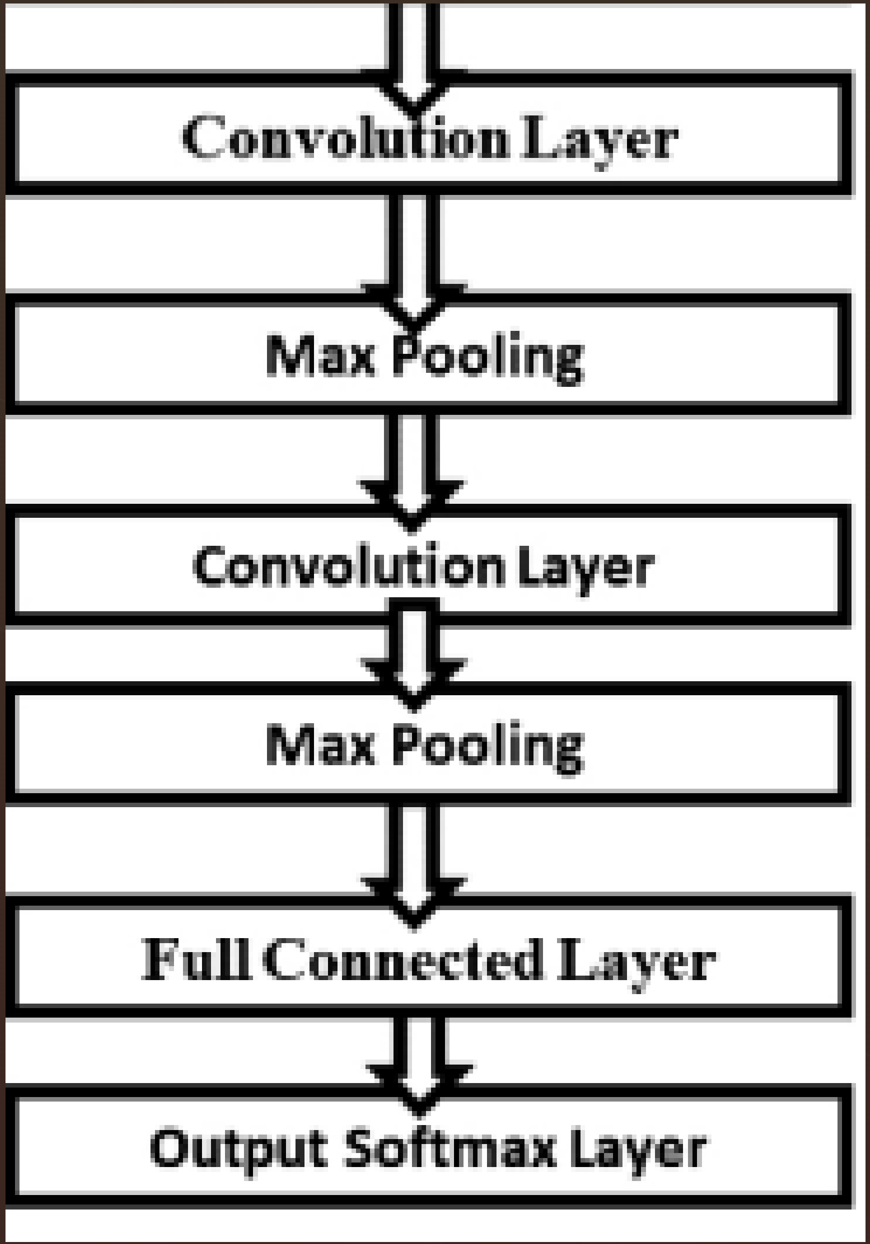
- Description of emotion classes:
  1. Anger
  2. Disgust
  3. Fear
  4. Happy
  5. Sad
  6. Surprise
  7. Neutral

Understanding the Convolutional Neural Network (CNN) Model Architecture

- CNNs are utilized as the backbone of the Student Concentration Analyzer.
- Hierarchical feature detection: CNNs automatically identify patterns on the face, aiding in emotion recognition.
- Translation Invariance: Emotions can be recognized regardless of their location in the image due to shared weights in convolutional layers.
- Feature Hierarchies: CNNs progressively learn higher-level features, enhancing the model's ability to discriminate emotions effectively.

Deep Emotion CNN Model Architecture

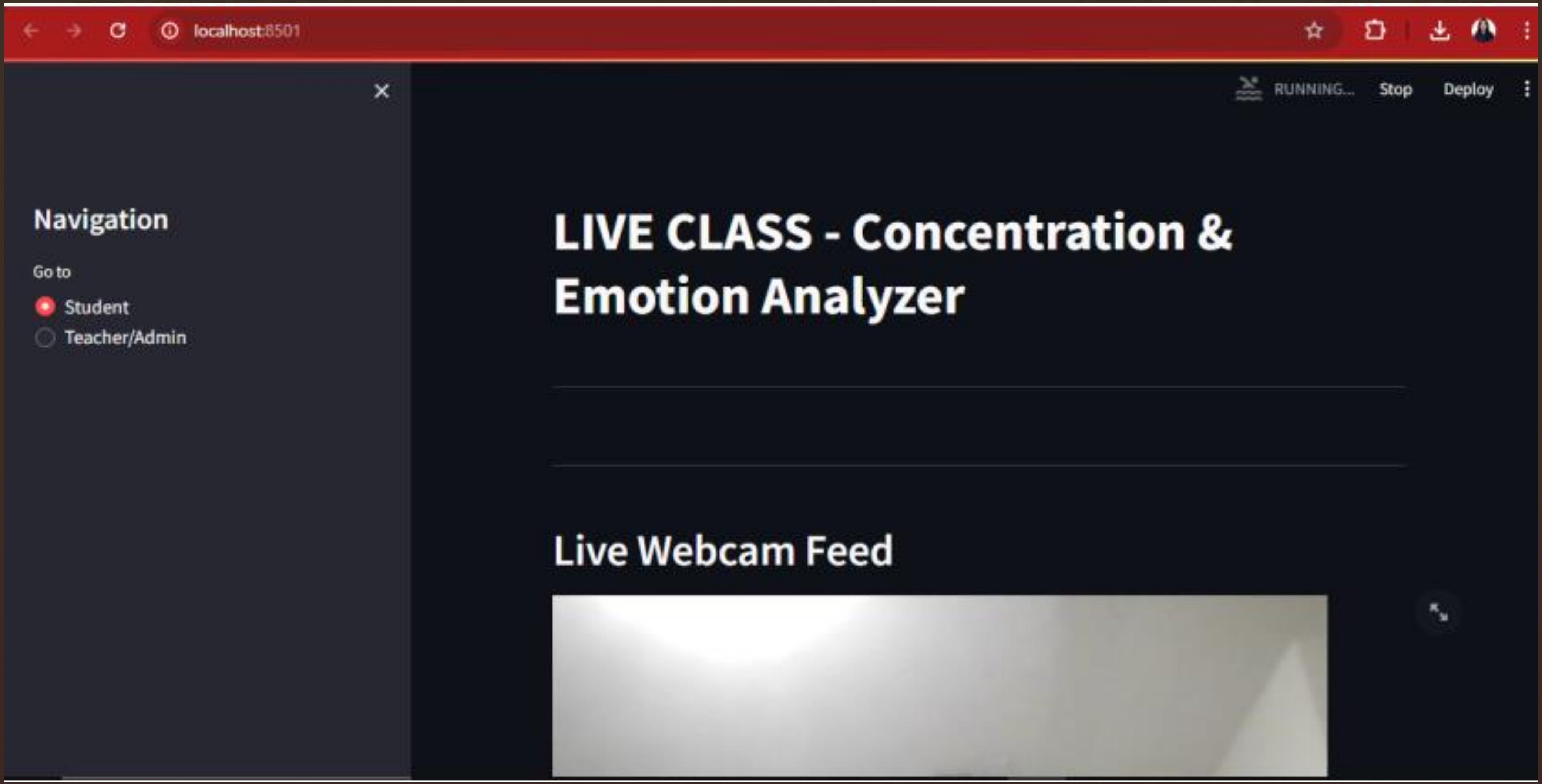
- Two convolutional layers (conv1 and conv2) with ReLU activation functions.
- MaxPooling layers (pool1 and pool2) for down sampling spatial dimensions.
- Dropout layers (self.dropout) to prevent overfitting by deactivating neurons during training.
- Three fully connected layers (fc1, fc2, and fc3) with Batch Normalization, ReLU activation, and Dropout.
- Final dense layer (fc3) with SoftMax activation function, comprising seven neurons for emotion classification.


Convolution Layer
Max Pooling
Convolution Layer
Max Pooling
Full Connected Layer
Output Softmax Layer

Training Process and Optimization Techniques

- Adam optimizer used for dynamic learning rate adjustment during training.
- Learning rate set to 0.0001 for optimized model training.
- Categorical cross-entropy loss function chosen for multi-class classification problem in emotion recognition.
- Development of a web application using Streamlit for user-friendly interaction with the emotion recognition system.

INTERFACE



localhost:8501
RUNNING...
Stop
Deploy
Navigation
Go to
Student
Teacher/Admin
LIVE CLASS - Concentration & Emotion Analyzer
Live Webcam Feed

EXPERIMENTS

TRAINING LOOP

7 FEATURES (PHASE 1)

EACH FEATURES (PHASE 2)

PHASE 1 EXPERIMENTS

- Utilization of the train_model function for training the CNN model over 30 epochs.
- Training on batches containing all 7 facial feature images combined.
- Adam optimizer employed for parameter adjustment and gradient propagation.
- Monitoring of training accuracy and validation loss for performance evaluation.
- Implementation of early stopping mechanism to prevent overfitting.
- Visualization of training and validation losses using Matplotlib plots for insights into model dynamics.

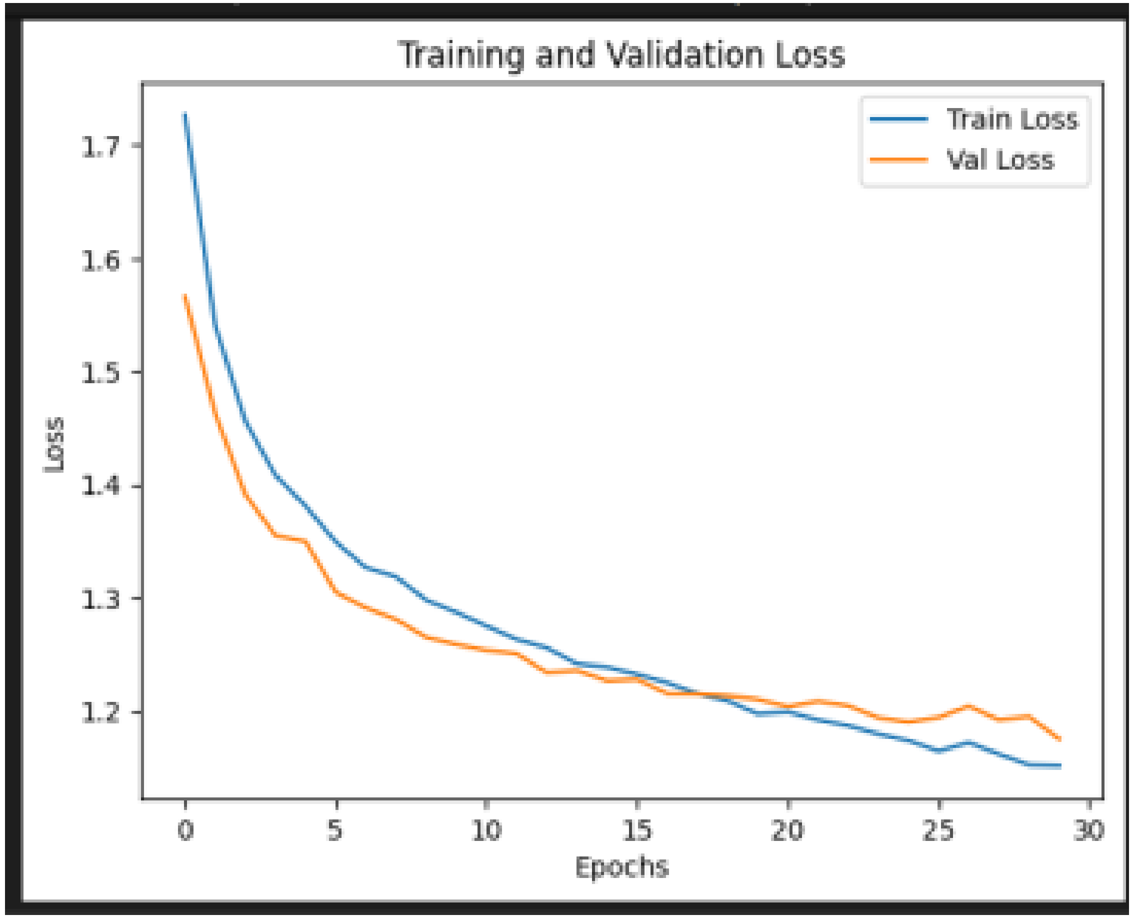
PHASE EXPERIMENTS

- Novel method of evaluating each facial feature batch individually.
- Fine-grained analysis enabling targeted optimizations for specific facial characteristics.
- Utilization of early stopping mechanisms to ensure optimal model generalization and mitigate overfitting.
- Visualization of training and validation dynamics for comprehensive performance assessment.
- Emphasis on the efficiency of phase 2 despite lower accuracy compared to phase 1.

COMPARING PHASE 1 AND 2

Aspect	Phase 1	Phase 2
Training Approach	Combined facial feature batches	Individual facial feature batches
Overfitting Risk	Observed	Mitigated through early stopping
Accuracy	Higher	Lower
Efficiency	Lower	Efficient despite lower accuracy
Early Stopping	Implemented	Implemented
Generalization	Risk of overfitting	Ensured through individual feature evaluation
Performance Evaluation	Training accuracy, validation loss	Comprehensive analysis of training dynamics
Optimization	Identifying trends, informed decisions	Targeted optimizations for specific features

PHASE 1:



PHASE 2:

Fig 7: **Training and Validation Loss**

CONFUSION MATRIX

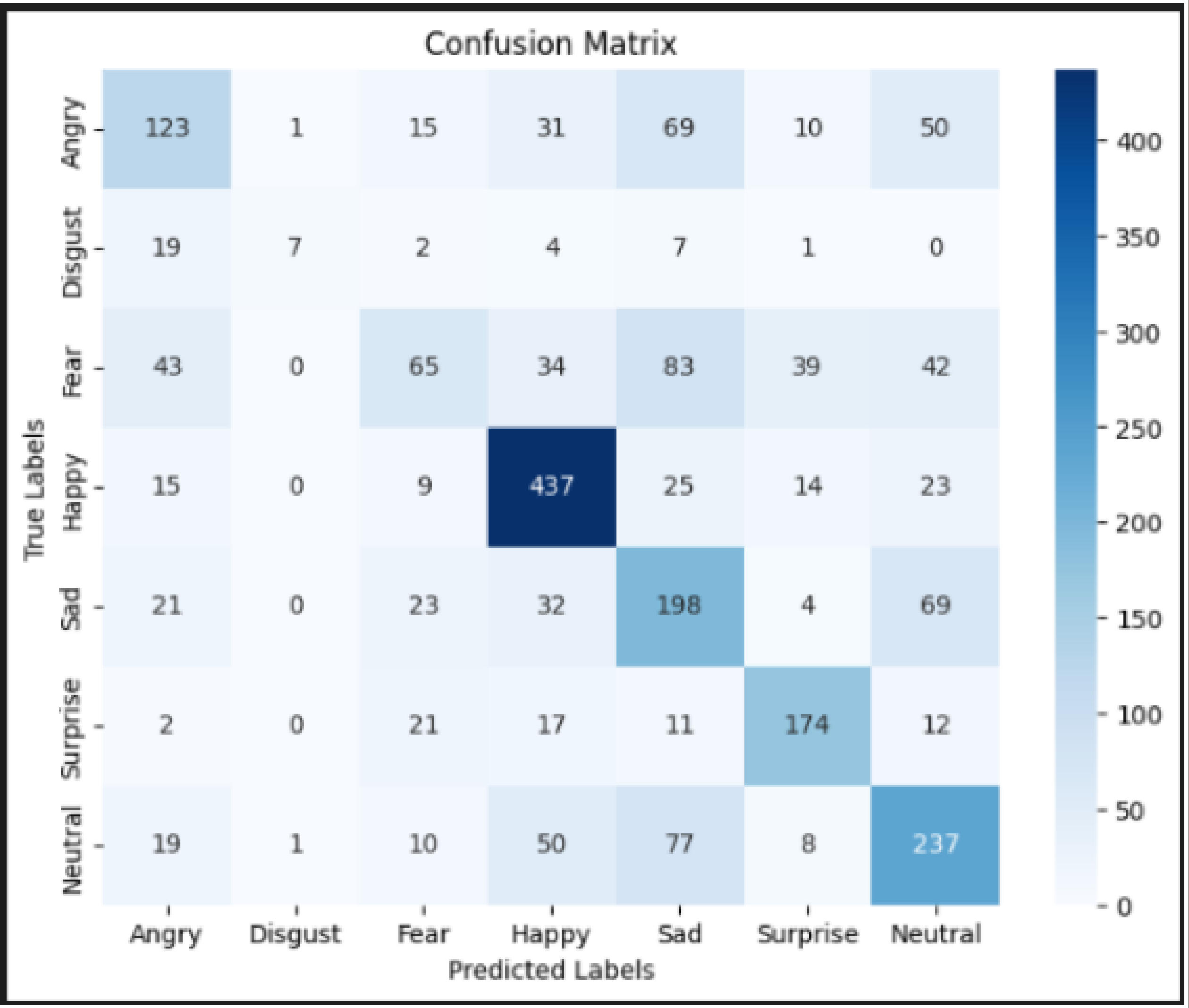


Fig 8 Confusion Matrix – Phase 1

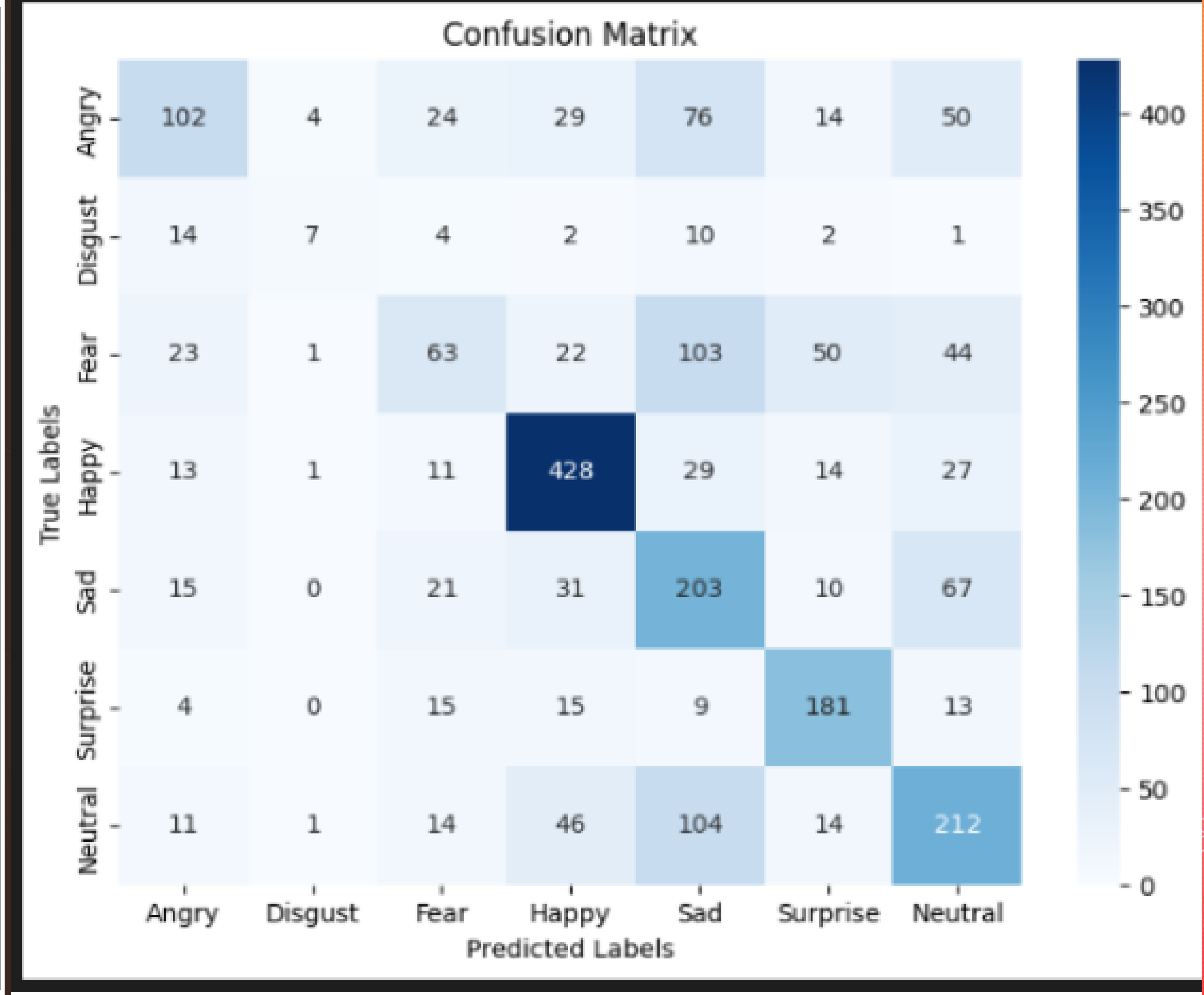


Figure 9: Confusion Matrix – Phase 2

PERFORMANCE METRICS

Performance Metrics Report:

Emotion	Precision	Recall	F1-Score	Support
Angry	0.51	0.41	0.45	299
Disgust	0.78	0.17	0.29	40
Fear	0.45	0.21	0.29	306
Happy	0.72	0.84	0.77	523
Sad	0.42	0.57	0.48	347
Surprise	0.70	0.73	0.71	237
Neutral	0.55	0.59	0.57	402
Average Weighted	0.57	0.58	0.56	-
Macro	0.59	0.50	0.51	-

Accuracy: 0.58

Figure 10: Performance Metric – Phase 1

Performance Metrics Report:

Emotion	Precision	Recall	F1-Score	Support
Angry	0.56	0.34	0.42	299
Disgust	0.50	0.17	0.26	40
Fear	0.41	0.21	0.28	306
Happy	0.75	0.82	0.78	523
Sad	0.38	0.59	0.46	347
Surprise	0.64	0.76	0.69	237
Neutral	0.51	0.53	0.52	402
Average Weighted	0.55	0.56	0.54	-
Macro	0.54	0.49	0.49	-

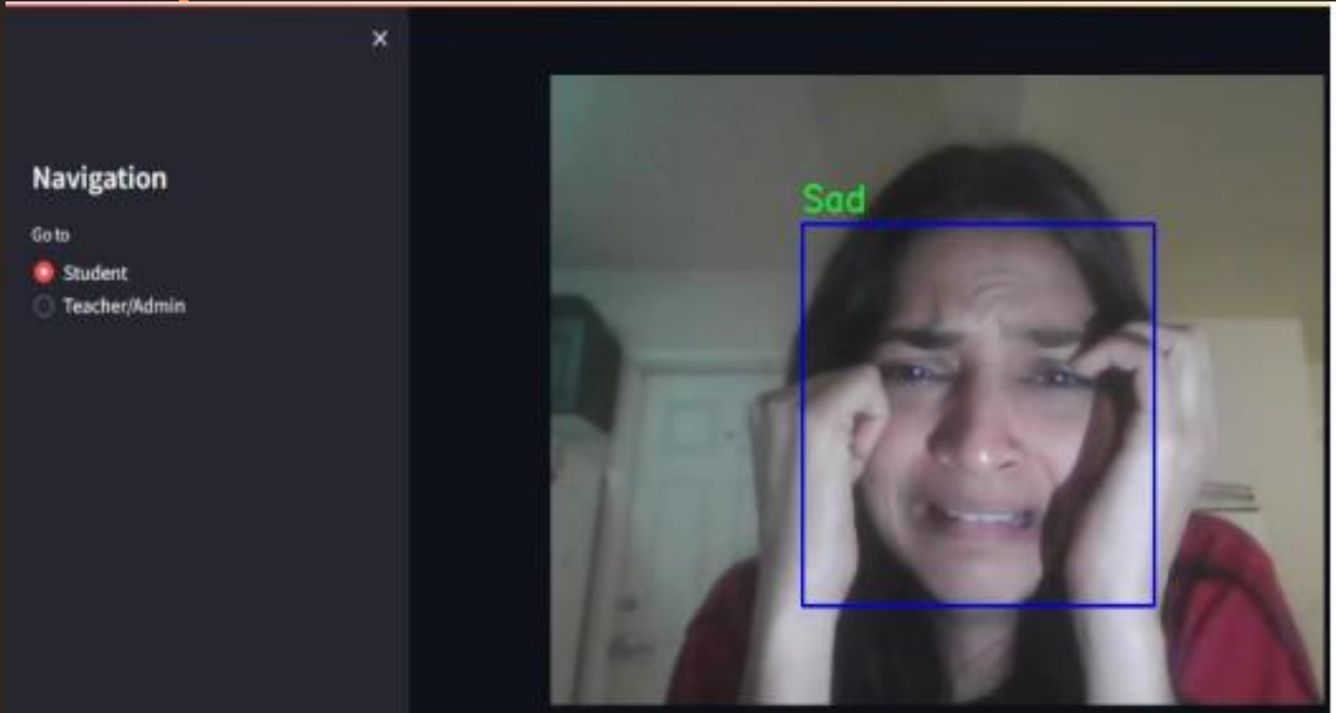
Accuracy: 0.56

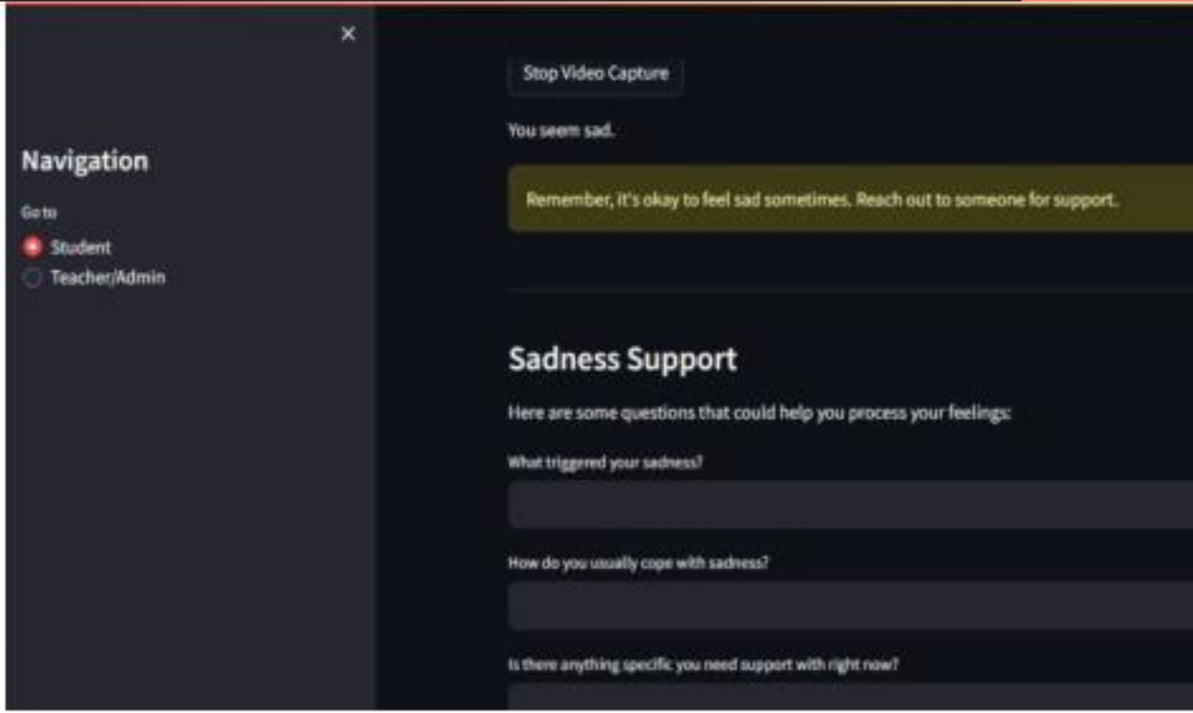
Figure 11: Performance Metric – Phase 2

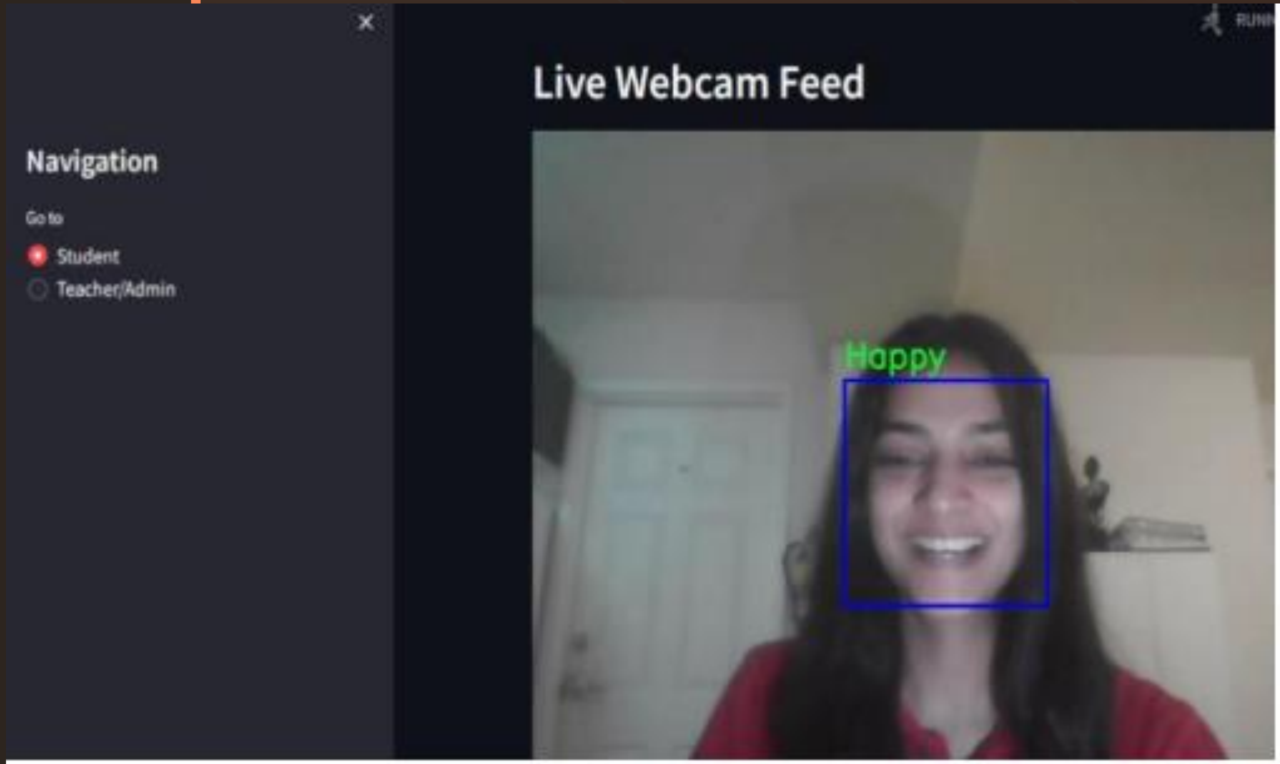
Limitations and Challenges

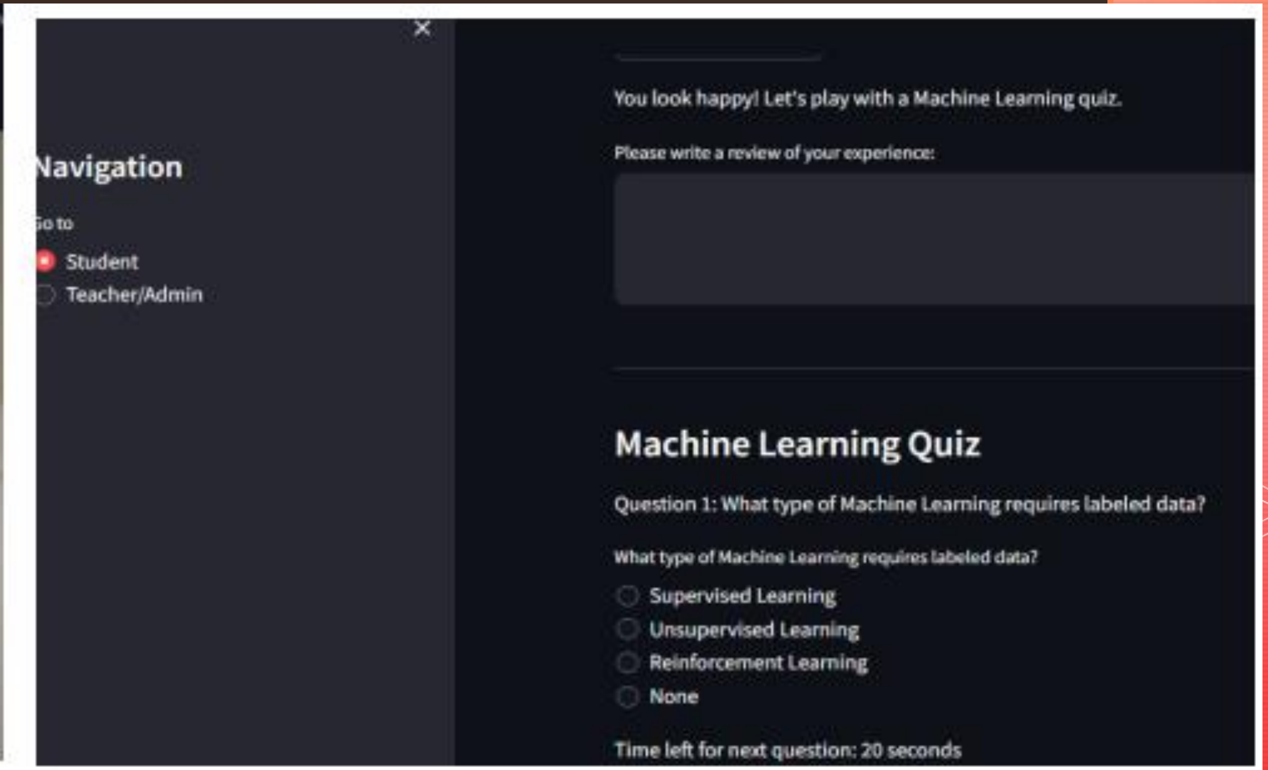
- Distinguishing between anger and disgust poses a challenge due to similar facial expressions.
- Lighting variations during testing can lead to inaccuracies.
- Emotion detection for multiple faces simultaneously may cause delays.
- Covered faces result in low accuracy as the system relies on facial features.
- Privacy concerns arise from using facial data as input.
- Generalizing to novel facial expressions is difficult due to wide variations.
- Future improvements may include better face recognition in dim-light and improved emotion differentiation.

RESULTS


Navigation
Go to
Student
Teacher/Admin
Sad


Navigation
Go to
Student
Teacher/Admin
Stop Video Capture
You seem sad.
Remember, it's okay to feel sad sometimes. Reach out to someone for support.
Sadness Support
Here are some questions that could help you process your feelings:
What triggered your sadness?
How do you usually cope with sadness?
Is there anything specific you need support with right now?


Live Webcam Feed
Navigation
Go to
Student
Teacher/Admin
Happy


avigation
o to
Student
Teacher/Admin
You look happy! Let's play with a Machine Learning quiz.
Please write a review of your experience:
Machine Learning Quiz
Question 1: What type of Machine Learning requires labeled data?
What type of Machine Learning requires labeled data?
Supervised Learning
Unsupervised Learning
Reinforcement Learning
None
Time left for next question: 20 seconds