Human Sentiment Analysis Using DenseNet-169: A Deep Learning Approach

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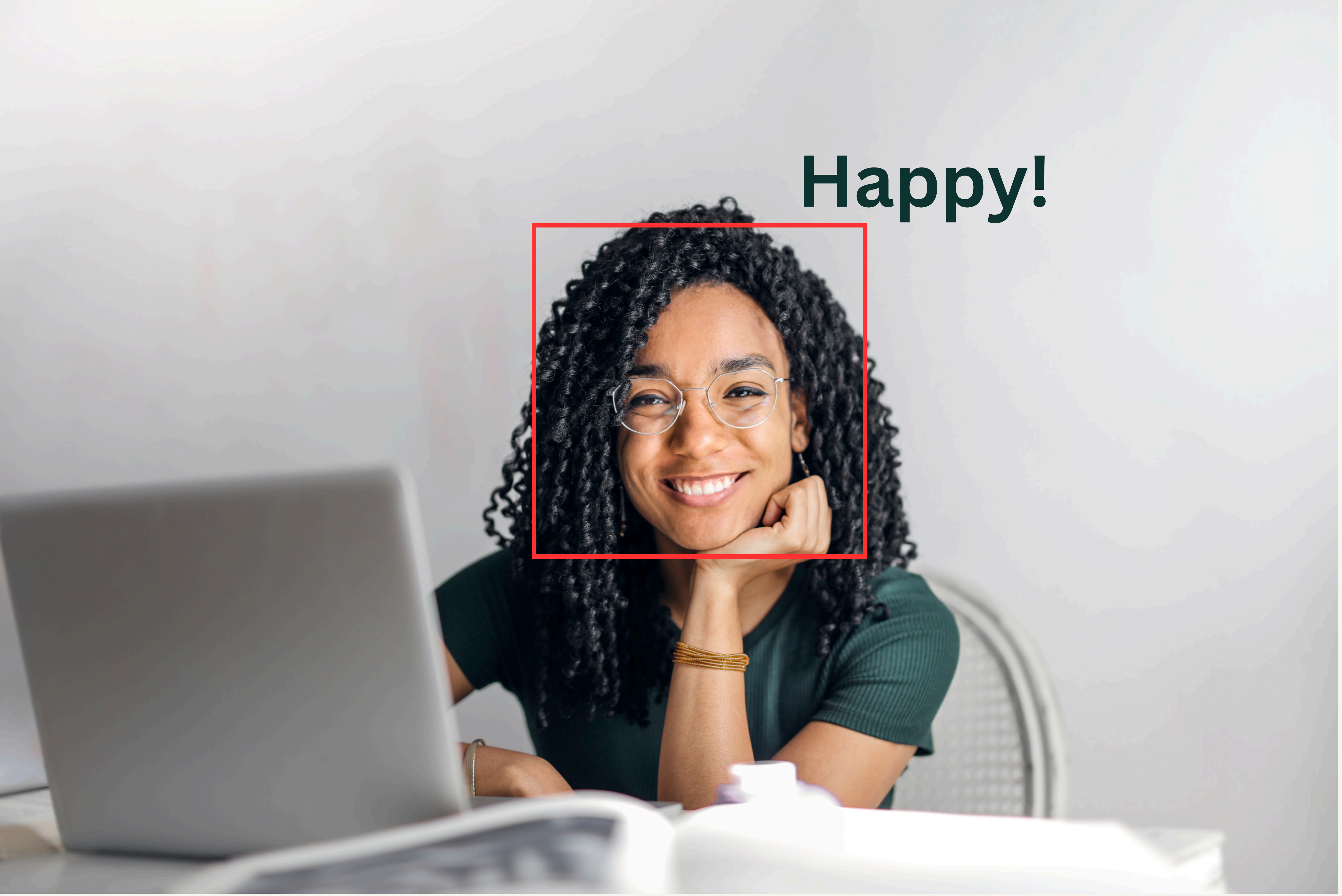
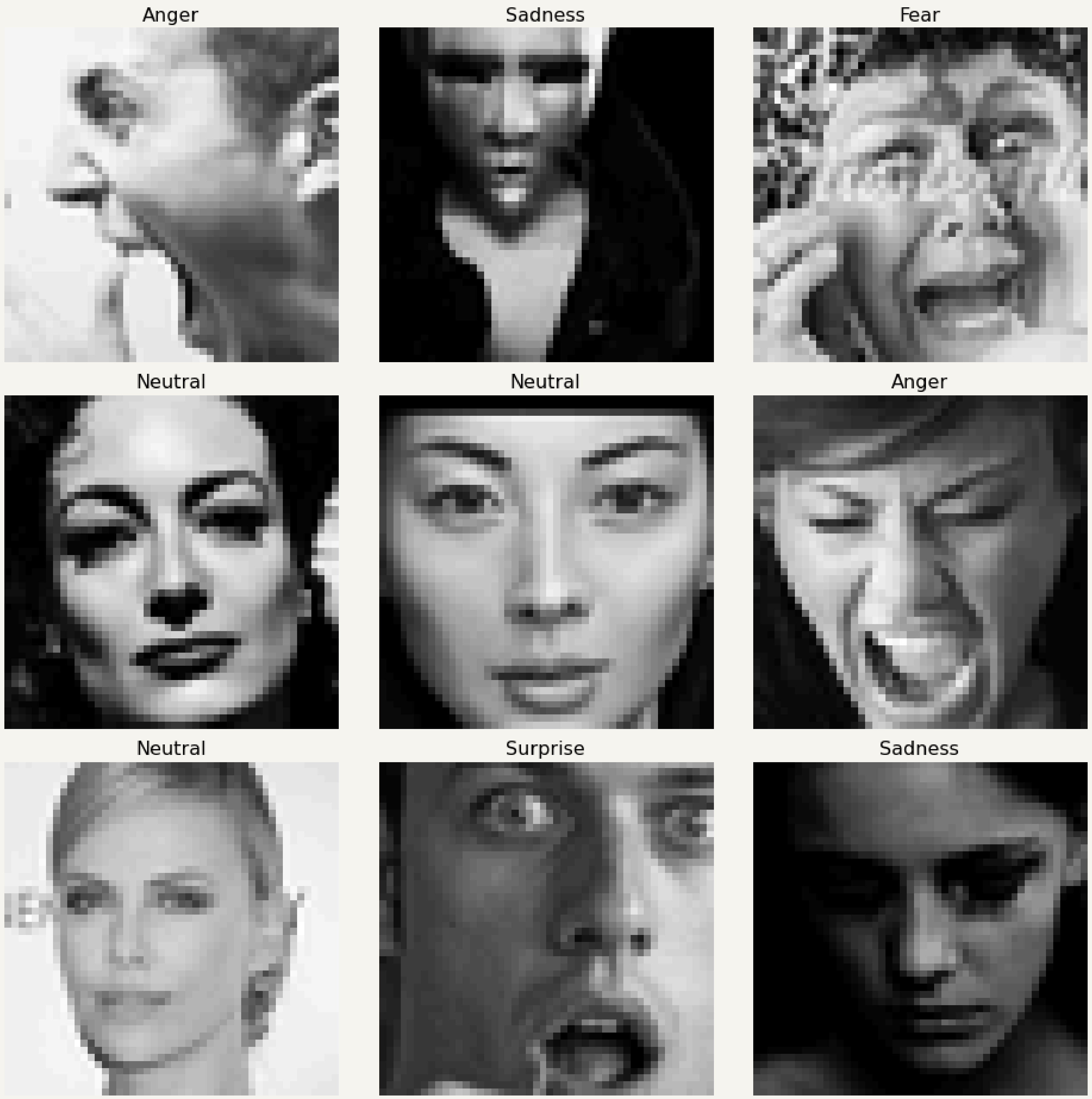


Your mood matters!

Introduction

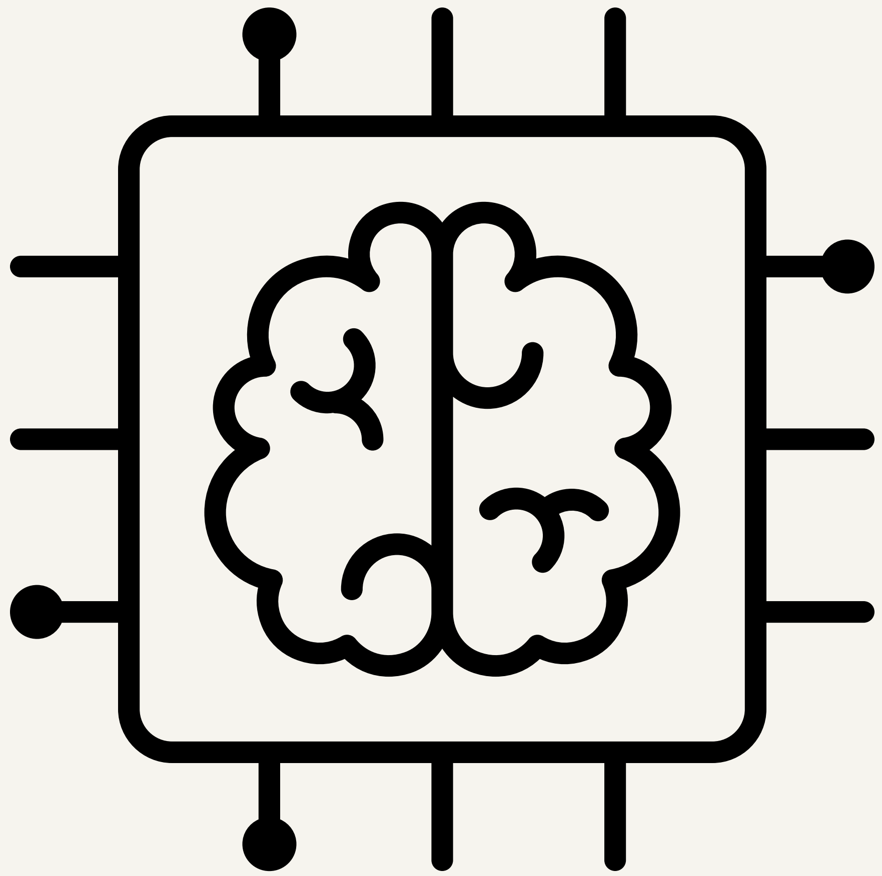
- Sentiment analysis of customer mood is critical for business insights.
- We used DenseNet-169 for efficient feature propagation and real-time analysis.
- **Objective**: Build a model to classify human emotion into multiple sentiment categories.



Why DenseNet-169?

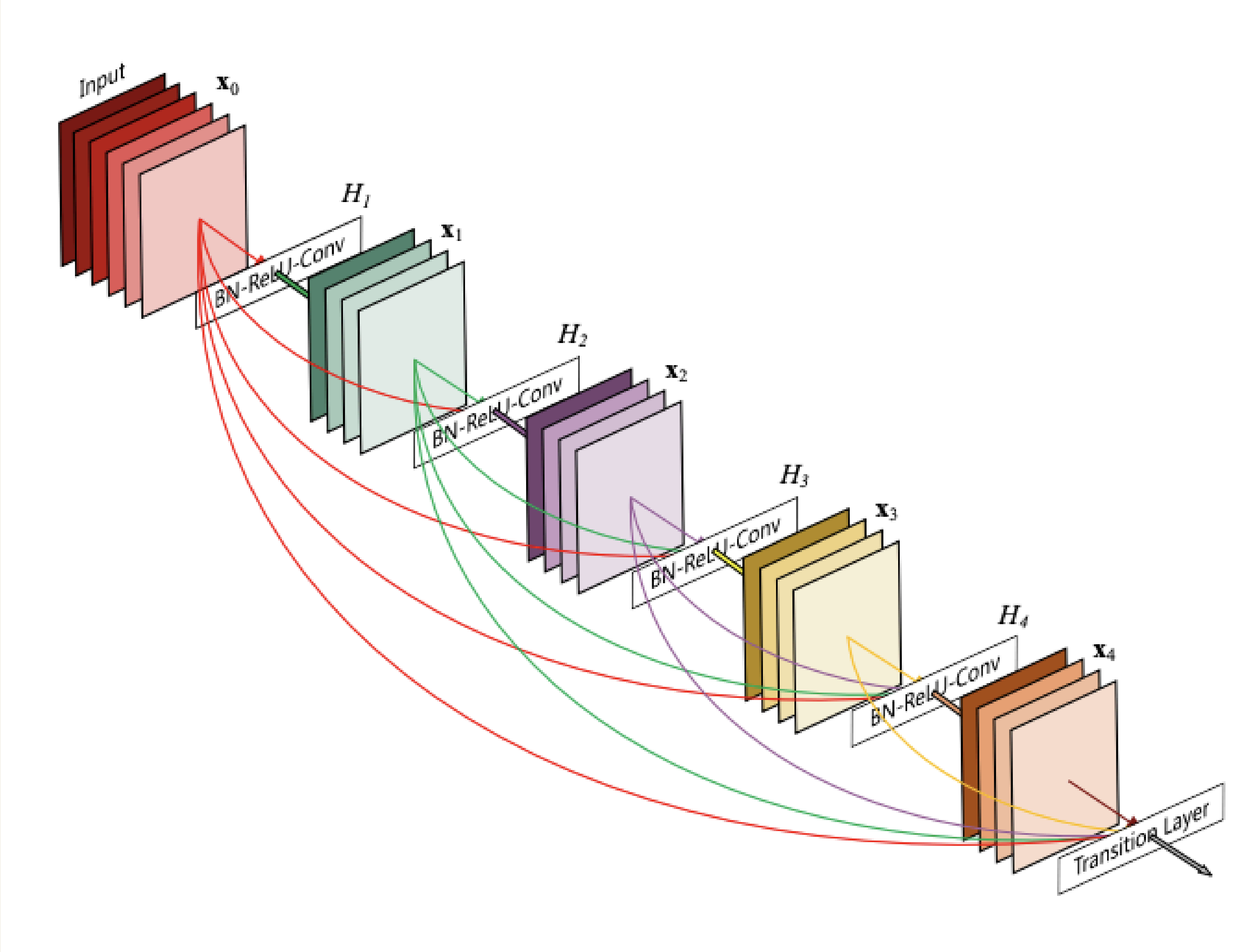
Key Points:

- Efficient feature reuse and parameter reduction.
- Solves vanishing gradient issues in deep networks.
- Suitable for real-time applications due to lightweight architecture.



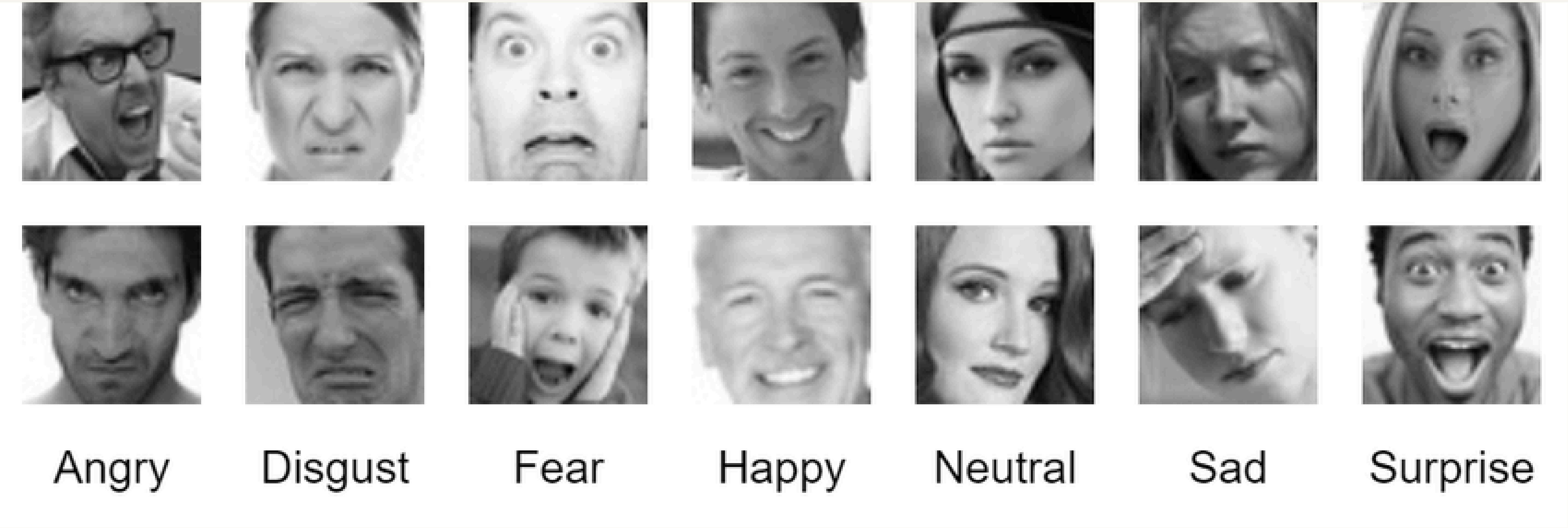
DenseNet-169 Architecture

- DenseNet-169 has four dense blocks with direct connections between all layers, enhancing feature learning at deeper levels.
- Dense blocks use batch normalization, ReLU, and 3x3 convolutions, while transition layers reduce dimensions with 1x1 convolutions and 2x2 pooling.
- The architecture solves vanishing gradient issues and improves parameter efficiency.
- With 14.3 million parameters, DenseNet-169 is more lightweight than ResNet-152, making it suitable for real-time tasks like sentiment analysis.



Data:

- **Dataset**: FER-2013 dataset was used, containing 35,887 grayscale images (48x48 pixels), categorized into seven emotions: anger, disgust, fear, happiness, sadness, surprise, and neutral.
- **Data Preprocessing:** TensorFlow's ImageDataGenerator, with DenseNet's preprocessing, was applied to standardize images for the model.



Data Preparation

- **Data Augmentation:** Techniques like horizontal flipping, width and height shifts, and rescaling were used to enhance model robustness.
- **Data Generators:** Three generators (training, validation, test) were created to load and augment images for each phase, aiming to improve model generalization.

DenseNet169 Transfer Learning

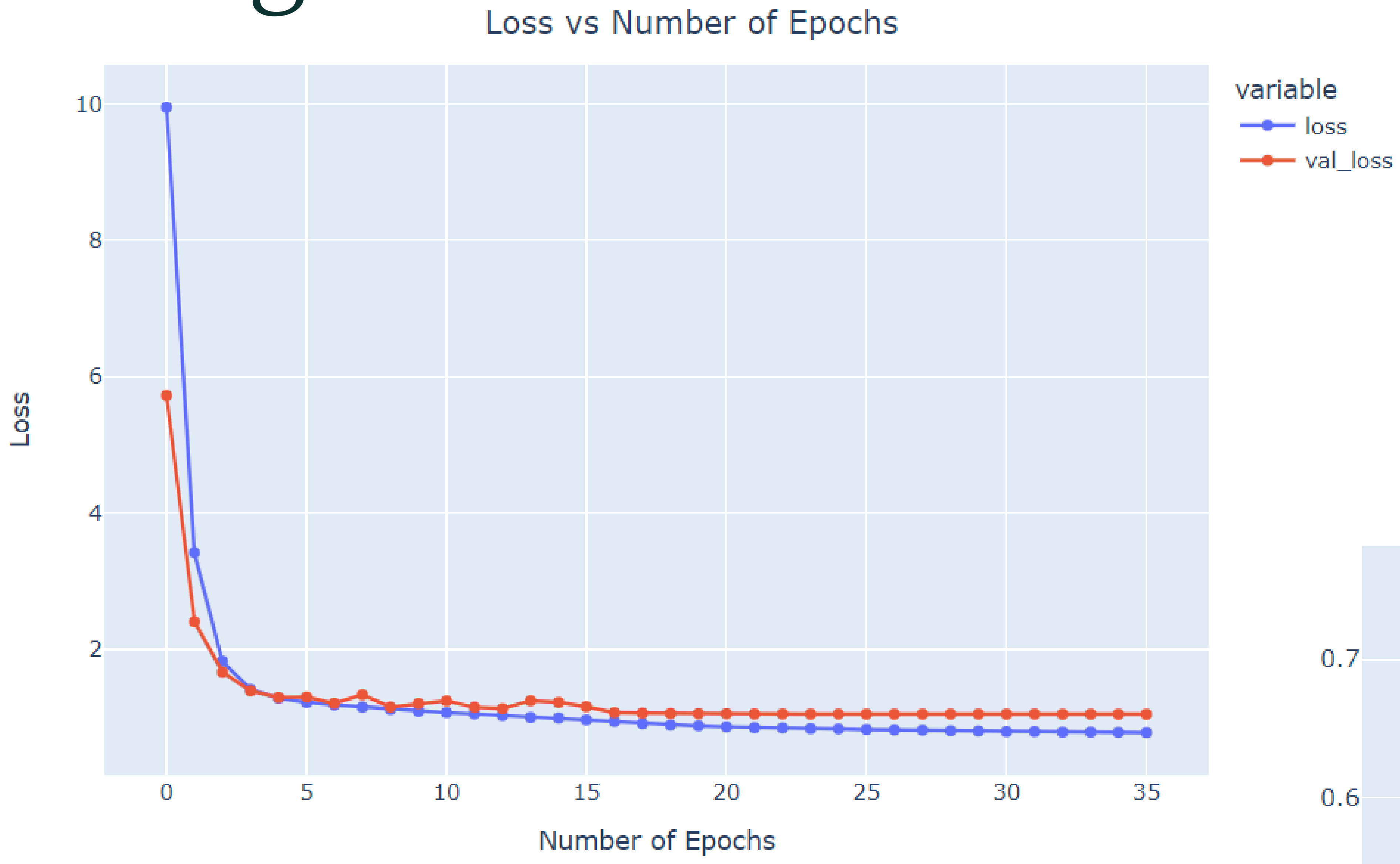
- **Data Augmentation:** Techniques like horizontal flipping, width and height shifts, and rescaling were used to enhance model robustness.
- **Data Generators:** Three generators (training, validation, test) were created to load and augment images for each phase, aiming to improve model generalization.

```
Model: "model"
_________________________________________________________________
Layer (type)Output Shape             Param #
=================================================================
input_1 (InputLayer)[(None, 48, 48, 3)]     0
_________________________________________________________________
densenet169 (Functional)(None, 1, 1, 1664)12642880
_________________________________________________________________
global_average_pooling2d (Gl (None, 1664)            0
_________________________________________________________________
dense (Dense)(None, 256)426240
_________________________________________________________________
dropout (Dropout)(None, 256)             0
_________________________________________________________________
dense_1 (Dense)(None, 1024)263168
_________________________________________________________________
dropout_1 (Dropout)         (None, 1024)            0
_________________________________________________________________
dense_2 (Dense)(None, 512)524800
_________________________________________________________________
dropout_2 (Dropout)(None, 512)             0
_________________________________________________________________
classification (Dense)(None, 7)3591
=================================================================
Total params: 13,860,679
Trainable params: 1,217,799
Non-trainable params: 12,642,880
```

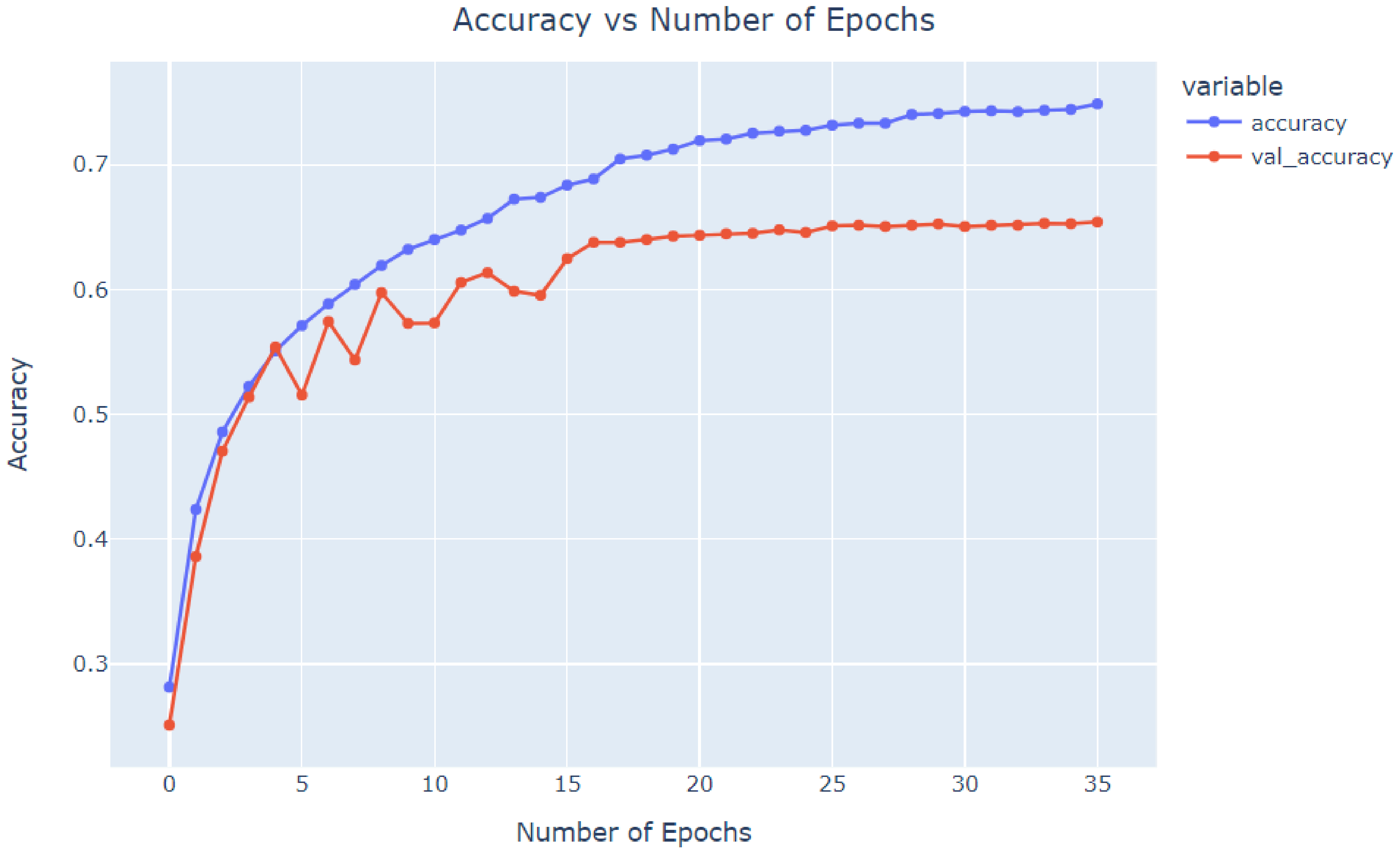
Training Process

DenseNet169 as Feature Extractor	The DenseNet169 architecture without the top layers was used.
Model Architecture	Dense layers with 256, 1024, and 512 units, followed by dropout layers, and a final softmax layer for 7 emotion classes.
Training Process	Initially froze DenseNet169 layers for 16 epochs, achieving 68.36 % accuracy.
Fine-Tuning	Unfroze DenseNet169 layers, fine-tuning with a lower learning rate, reaching 74.86% accuracy after 20 additional epochs.
Validation	Validation accuracy stayed at 65.41 %
Key Importance	This two-step training approach allowed us to gradually enhance the model's ability to classify emotions effectively, combining the strengths of transfer learning with targeted fine-tuning.

Figures



After fine tuning, the accuracy increased, and validation accuracy reached 65.41%



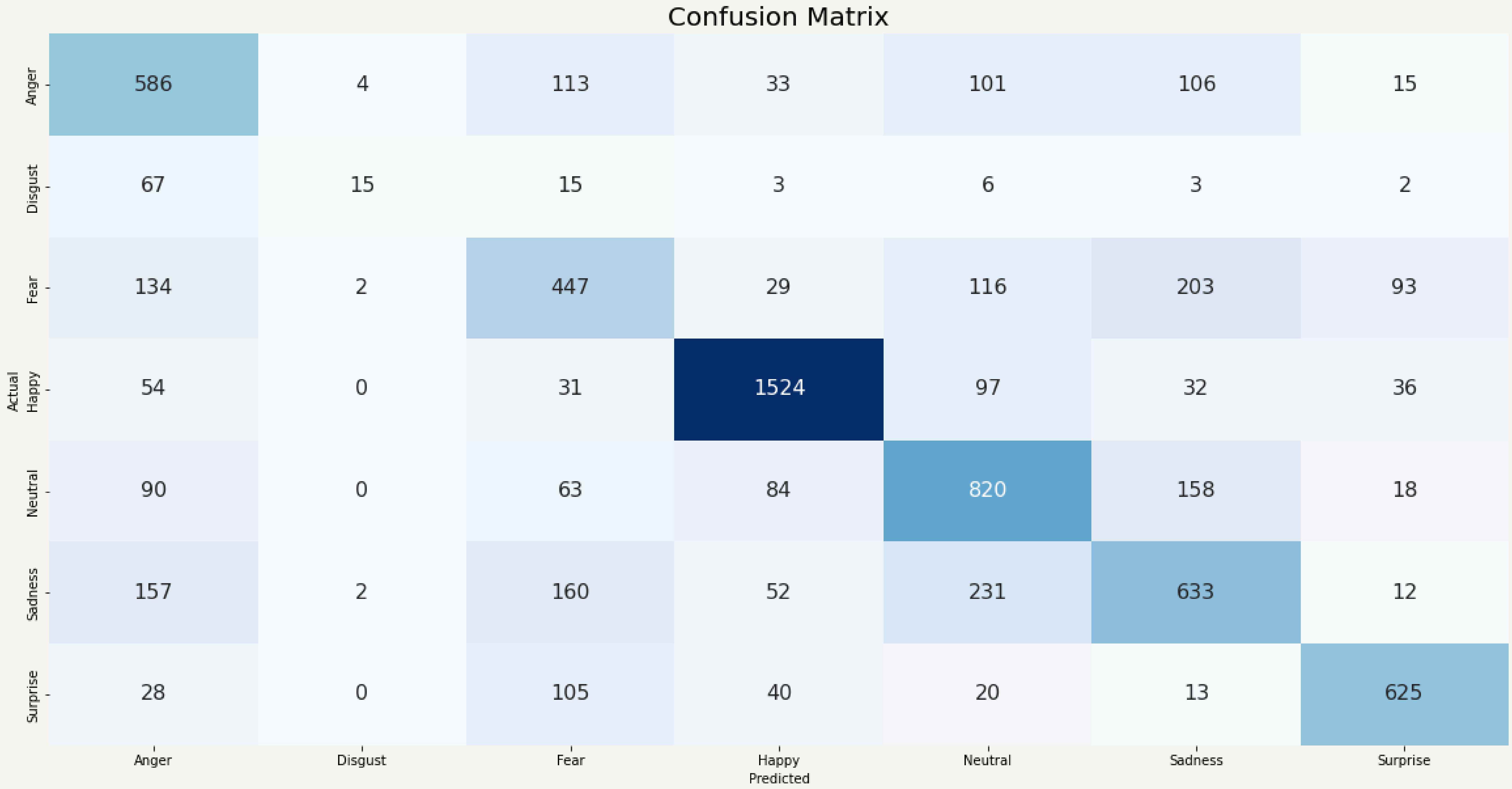
Over 16 epochs, we saw a significant boost in accuracy, climbing from 28.17% in the first epoch to 62.46% by the end, while the validation loss steadily decreased.

Model Evaluation

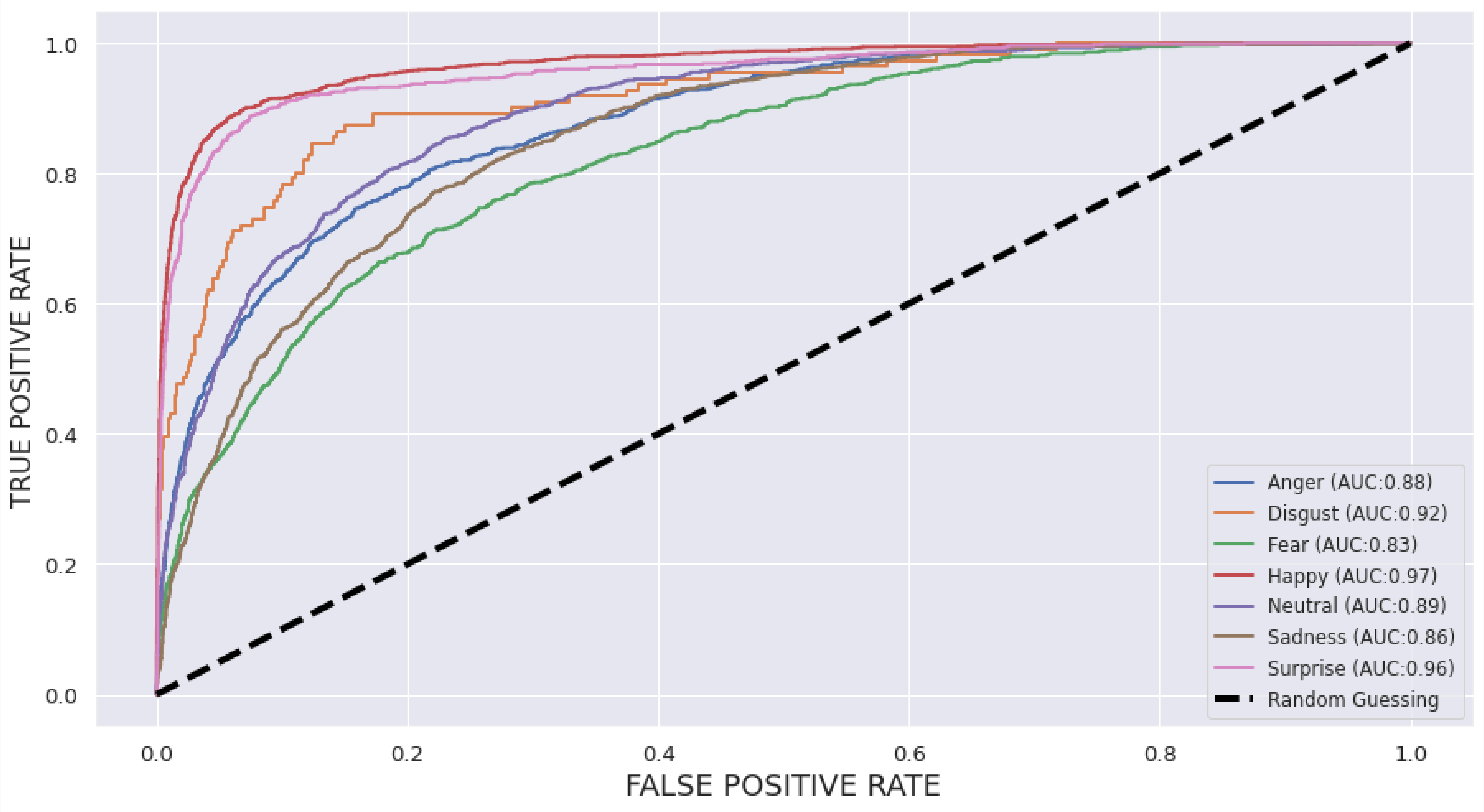
Model Performance	Achieved an accuracy of 64.78% with a loss of 1.0661 on unseen test data.
Confusion Matrix	Visualized using a heatmap to show correct versus misclassified predictions for each emotion category.
Classification Report	Precision, recall, and F1-score were calculated, with an overall accuracy of 65% and a weighted F1-score of 0.64.
Multiclass ROC AUC	Achieved an ROC AUC score of 0.92, indicating strong performance in classifying emotions.

class	precision	recall	f1-score	support
0	0.53	0.61	0.57	958
1	0.65	0.14	0.22	111
2	0.48	0.44	0.46	1024
3	0.86	0.86	0.86	1774
4	0.59	0.67	0.62	1233
5	0.55	0.51	0.53	1247
6	0.78	0.75	0.77	831
accuracy			0.65	7178
macro avg	0.63	0.57	0.58	7178
weighted avg	0.65	0.65	0.64	7178

Confusion Matrix



ROC AUC


1.0
0.8
0.6
0.4
0.2
0.0
TRUE POSITIVE RATE
0.0
0.2
0.4
0.6
0.8
1.0
FALSE POSITIVE RATE
Anger (AUC:0.88)
Disgust (AUC:0.92)
Fear (AUC:0.83)
Happy (AUC:0.97)
Neutral (AUC:0.89)
Sadness (AUC:0.86)
Surprise (AUC:0.96)
Random Guessing

Discussion:

- DenseNet169 effectively addresses the vanishing gradient problem and improves feature propagation.
- Achieved ~65% accuracy, performing well despite the complexity of emotion classification.
- Confusion matrix shows challenges in differentiating visually similar emotions.
- High ROC AUC scores (0.92) confirm strong classification performance across emotional categories.

Conclusion:

- DenseNet169 successfully extracts intricate emotional features, with solid overall performance.
- Challenges remain in accurately classifying emotions.
- Future improvements should target these misclassifications for better accuracy.

Thank You!