

Real-Time Emotion-Based Concentration Estimation: Na Educational Framework withLightweigth Neural Networks

Edward Junior<sup>1</sup>, Daniel Guzmán<sup>1</sup>, Miguel Postigo<sup>1</sup>, Israel Torné<sup>1</sup>

1 PPGEEL- Postgraduate Program in Electrical Engineering, School of Technology, State University of Amazonas (UEA), Manaus 69050-020, Brazil

INTRODUCTION & AIM

Artificial Intelligence (AI) education often presents challenges for beginners, as concepts such as neural networks and computer vision can seem abstract. This work proposes a **real-time facial emotion-based concentration monitoring system** designed as a didactic tool to help students understand AI through hands-on experimentation. The framework integrates **computer vision** and **lightweight neural networks** to classify emotions and infer concentration levels. Its main goal is to demonstrate that even **simple CNN architectures** can achieve functional and interpretable results using limited computational resources. By linking emotional recognition to concentration estimation, the system promotes both technical and conceptual learning, helping students connect AI algorithms to human behavior analysis.

METHOD

The system uses **OpenCV** for real-time video capture and face detection through the **Haar Cascade Classifier**. Detected faces are converted to grayscale, resized to **48×48 pixels**, and normalized for model inference. Emotion classification is performed by a **lightweight CNN** trained on the **FER2013 dataset**, which contains over **25,000 images** labeled across seven emotion classes: *anger*, *disgust*, *fear*, *happiness*, *neutrality*, *sadness*, and *surprise*. Based on the predicted emotion, a **rule-based logic** estimates concentration levels as *high*, *medium*, or *low*. For instance, *neutral* and *sad* indicate higher concentration, *happy* and *surprised* reflect moderate focus, and *angry*, *fearful*, or *disgusted* suggest low attention. This mapping aligns with findings in **educational psychology** that associate emotional states with cognitive engagement. The framework runs efficiently on standard hardware, offering **real-time inference** without GPU acceleration. Its modular and accessible design makes it ideal for **educational use**, enabling students to visualize the relationship between emotion and concentration in applied AI experiments.



FER-2013

Learn facial expressions from an image

Data Card Code (742) Discussion (8) Suggestions (6)

About Dataset

The data consists of 48×48 pixel grayscale images of faces. The faces have been automatically registered so that the face is more or less centred and occupies about the same amount of space in each image.

The task is to categorize each face based on the emotion shown in the facial expression into one of seven categories (0=Angry, 1=Disgust, 2=Fear, 3=Happy, 4=Sad, 5=Surprise, 6=Neutral). The training set consists of 28,709 examples and the public test set consists of 3,589 examples.



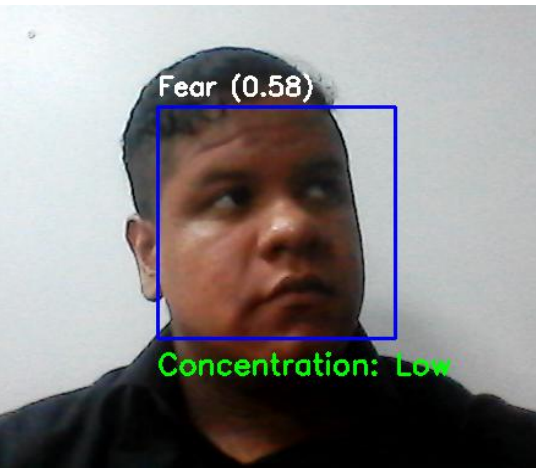
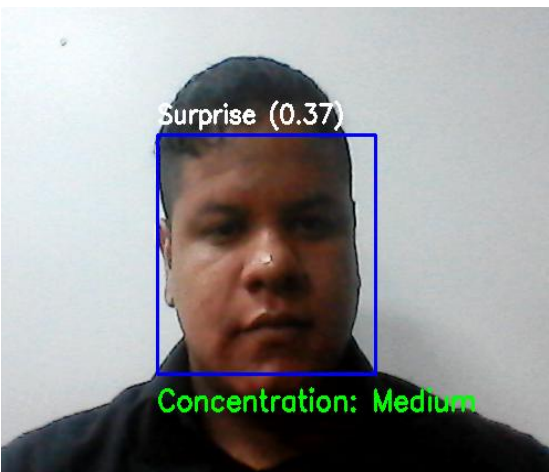
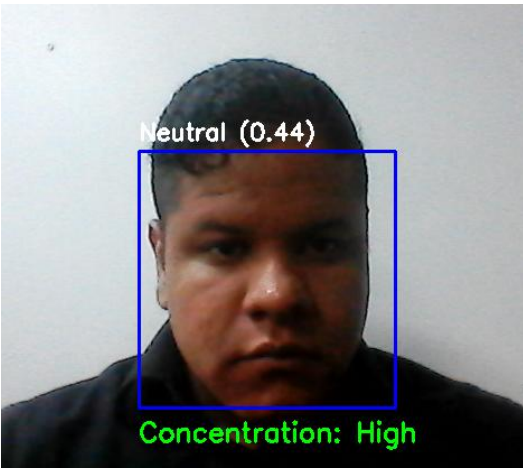
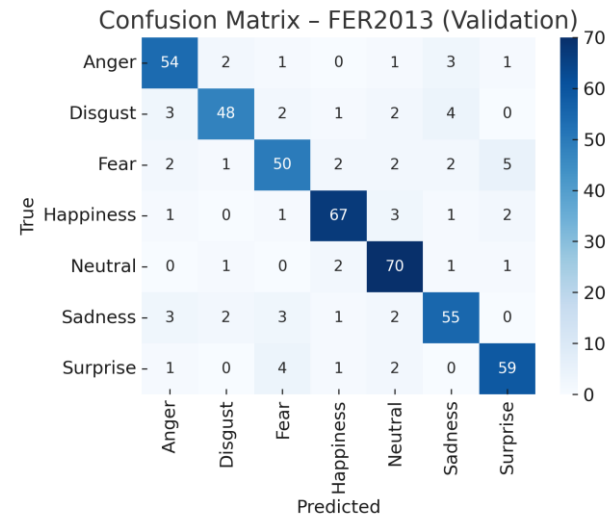
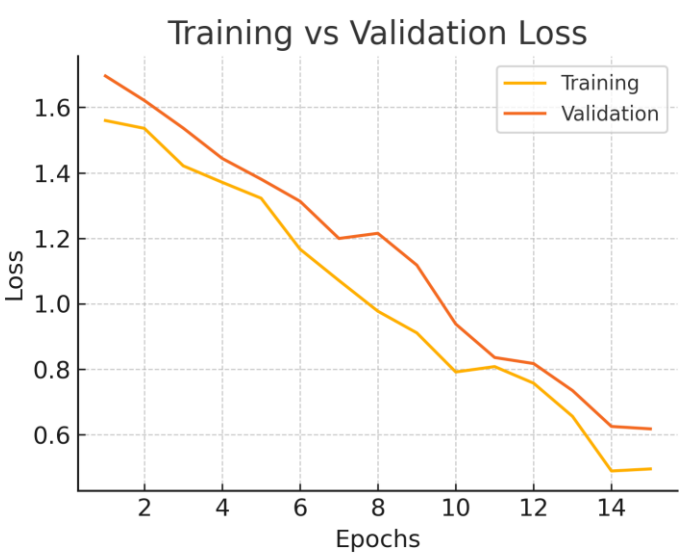
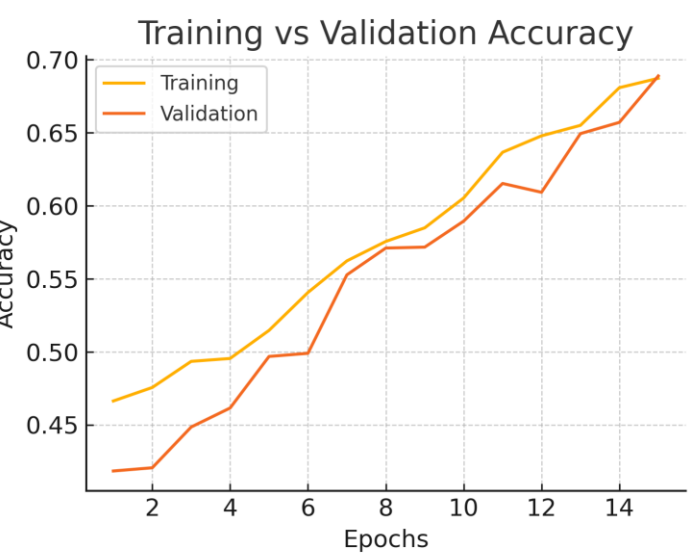
Usability 750

License Database: Open Database, Cont...

Expected update frequency Not specified

RESULTS & DISCUSSION

The trained **CNN model** reached approximately **70% accuracy** on the FER2013 validation set, providing reliable real-time emotion recognition at around **20 frames per second**. Training and validation curves showed stable convergence without overfitting, confirming the suitability of the simplified architecture. The **confusion matrix** indicated stronger performance in detecting *happiness* and *neutrality*, with occasional overlap between *fear* and *surprise*. The **rule-based concentration estimator** effectively mapped detected emotions to *high*, *medium*, or *low* attention levels, generating intuitive and consistent results. Classroom demonstrations showed that students gained a clearer understanding of **AI inference** and **emotion-to-behavior mapping** through live visualization. The system remained robust under different lighting and facial orientations. Overall, these findings validate the potential of **lightweight neural networks** for accessible, emotion-based concentration analysis in educational and interactive contexts.



CONCLUSION

This work bridges **AI theory and practice** through an accessible emotion-based concentration monitoring framework. The model shows that small-scale neural networks trained on FER2013 can deliver meaningful results while remaining computationally efficient. The project encourages students to experiment with real-time inference, emotion recognition, and behavioral interpretation, deepening their understanding of AI workflows. Beyond its pedagogical value, the system promotes reflection on the role of emotional intelligence in human–computer interaction. By merging simplicity, interpretability, and functionality, this framework becomes a powerful tool for **AI literacy** and **educational innovation** in technology learning environments.

REFERENCES

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