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Design Assessing Pre-Exam Nervousness Levels in Students Using Neural Network for Emotion Recognition

Edward Junior[1], Daniel Guzmán[1], Miguel Postigo[1], Israel Torné[1]

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

INTRODUCTION & AIM

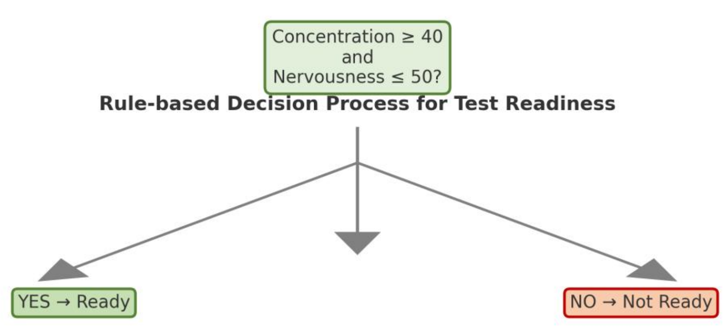
Nervousness is one of the most influential emotional factors affecting academic performance, especially in **high-stakes evaluations**. Excessive anxiety before or during exams can reduce concentration, impair decision-making, and hinder learning outcomes. Understanding and monitoring this emotional variable can help educators design fairer and more adaptive assessment environments. This work proposes a **neural network–based framework** to estimate and monitor students' nervousness levels in pre-exam scenarios. The system applies **facial emotion recognition** to quantify emotional tension and generate interpretable nervousness scores. The primary aim is to provide educators with a reliable tool to identify students experiencing excessive stress and promote a more balanced emotional state before testing.

METHOD

The framework employs a **Convolutional Neural Network (CNN)** trained on the **FER2013 dataset**, comprising over **25,000 grayscale facial images** across seven emotions. Using **OpenCV**, real-time video frames are captured, converted to grayscale, resized to **48×48 pixels**, and normalized for inference. Each detected emotion is translated into two quantitative indicators—**concentration** and **nervousness**—ranging from 0 to 100. Weighted emotion coefficients define their influence: *neutral* and *happy* increase concentration, while *fear, anger,* and *sadness* elevate nervousness. The system updates these indicators dynamically for each question, averaging results to assess emotional readiness. A **rule-based function** classifies the student as *ready* when concentration ≥ 40 and nervousness ≤ 50. After all ten questions, overall readiness is confirmed if six or more are classified as ready. This process reflects psychological evidence linking affective states to attention and performance, enabling interpretable emotional tracking for educational evaluation. This methodology, grounded in **psychology and educational research**, reflects the relationship between affective states, focus, and performance during assessments, enabling interpretable and adaptive emotional analysis in learning contexts.

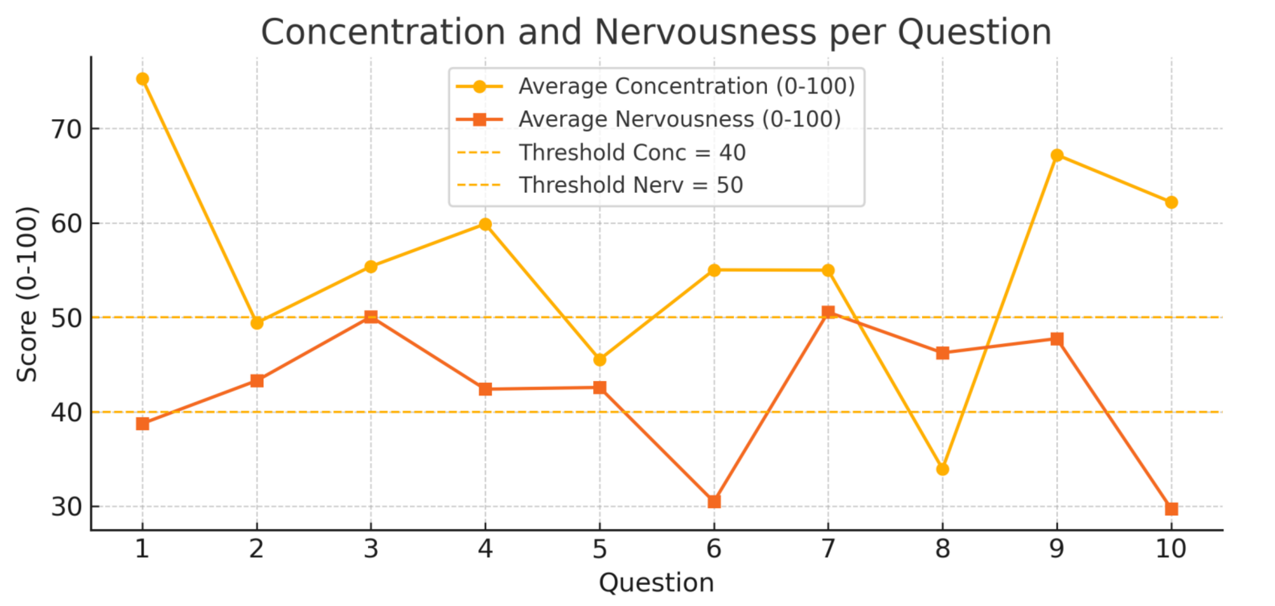
Weighted Mapping of Emotions to Concentration and Nervousness

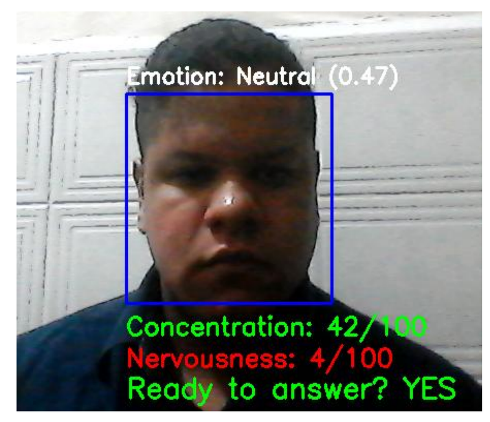
Emotion	Concentration Weight	Nervousness Weight
Anger	0.2	0.9
Disgust	0.3	0.7
Fear	0.1	1.0
Happiness	0.6	0.3
Neutral	0.9	0.1
Sadness	0.8	0.2
Surprise	0.5	0.6

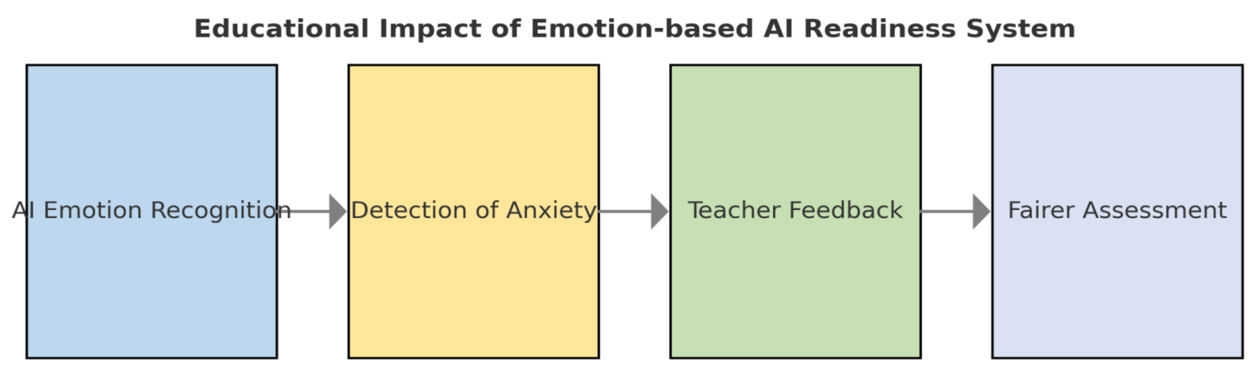


RESULTS & DISCUSSION

The CNN reached approximately **70% accuracy** on the FER2013 dataset, providing stable emotion recognition across different lighting and facial conditions. The **weighted scoring system** successfully quantified concentration and nervousness, generating interpretable 0–100 indicators for each question. Students expressing *neutral* or *happy* emotions showed higher concentration, while *fear, anger,* and *sadness* increased nervousness. The **rule-based function** determined readiness when concentration ≥ 40 and nervousness ≤ 50. Across ten questions, overall readiness was achieved when at least six met this condition. Results demonstrated consistent alignment between emotional states and behavioral patterns, confirming the framework's effectiveness for **non-invasive, real-time readiness analysis** in educational settings.







CONCLUSION

This study demonstrates that **neural networks** can effectively quantify students' nervousness levels and provide valuable insights into emotional readiness before exams. By integrating facial emotion recognition with a weighted scoring model, the framework transforms subjective stress indicators into measurable data. The results validate the system's potential as a **decision-support tool** for educators, helping identify learners who may need additional emotional support. Beyond detection, this approach promotes reflection on emotional well-being and its role in academic success. The research contributes to **affective computing in education**, highlighting how AI can foster fairness, empathy, and adaptability in modern assessment practices.

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