

Smart Education Platform: Based on Emotions Content Delivery Using ML

Dr. N. Rajasekhar Reddy¹; Govardhan N.²; Gokul N.³; Karthik E.⁴; Manoj M.⁵

¹Professor, CSE (Artificial & Machine Learning), Don Bosco Institute of Technology Bengaluru, India.

²CSE (Artificial & Machine Learning), Don Bosco Institute of Technology Bengaluru, India.

³CSE (Artificial & Machine Learning), Don Bosco Institute of Technology Bengaluru, India.

⁴CSE (Artificial & Machine Learning), Don Bosco Institute of Technology Bengaluru, India.

⁵CSE (Artificial & Machine Learning), Don Bosco Institute of Technology Bengaluru, India.

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Abstract: This project proposes a Smart Education Platform that dynamically adapts online learning content based on students' real-time emotions to improve engagement and outcomes. Leveraging multimodal inputs—facial expressions detected via webcam using ResNet, speech sentiment analysis through Wav2Vec, and contextual surveys the system identifies states such as engagement, boredom, and annoyance. Integrated within a Flask based web application and Moodle, a reinforcement learning agent tailors interventions (quizzes, lessons, condensed material) by optimizing a reward function (+1 for engagement, -1 for negative emotions). Privacy is prioritized through webcam opt-out, on-device processing, and informed consent. The solution was validated on 20–50 learners using AffectNet and other datasets, achieving high accuracy with fivefold cross-validation. The system provides personal, scalable, and privacy-aware experiences in a variety of educational contexts, addressing the limitations for static learning platforms. A focus on emotional agility enhances efficiency and motivation, setting a standard for future massive deployment and human-centered digital learning.

Keywords: Regulatory Fit Theory, Fuzzy Logic, Smart Education, Personalized Learning.

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I. INTRODUCTION

Emotion recognition and Machine Learning Introduction Today, students are more independent and have access to knowledge created by web-based learning environments such as Moodle. Their learning practices have changed in a big way. Students' mood, which is a relevant variable that has an impact on their motivation and performance, is normally neglected by the traditional educational administration model, tending to offer static content. While frustrations, feeling uncomfortable, or being engaged may affect learning by the students, most systems are unable to detect and respond to such emotional signals in real-time. In order to bridge this chasm and enhance motivation with success, this chasm points towards the need for intelligent and adaptive platforms that are capable of personalization in learning processes based on emotional input. To solve this problem, Sentiment-Aware Learning Systems for Responsive Education Platforms establish the construction of a model capable of joining adaptive content adaptation with real-time emotional assessment. The architecture detects feelings of boredom, dissatisfaction, and engagement based on multimodal information that includes

looks through webcam recording; processes with ResNet; audio sentiment analysis with Wav2Vec; and Surveys contextual. To maximize participation, an integrated reinforcement learning agent in a Flask-based online application along with Moodle selects interventions such as recommended tutorials, summarized content, or interactive tests. The reward mechanism of the RL agent concentrates positive emotional states, ensuring personalized responses based on the requirements of each user. With a concern for privacy, the system contains on-device data processing, opt-out possibilities for webcams, and tight moral standards that include informed consent. It was tested on a sample of 20-50 students and utilizes databases like Affect Net and RAVDESS for robust emotion detection that has been validated through tough criteria. It seeks to remake online education for the future by resolving the deficiency of static educational platforms and setting up a scalable human-centered learning environment, thus improving the performance and motivation of students in both synchronous and asynchronous conditions.

II. LITERATURE SURVEY

To improve classroom presentations, the "Towards Emotionally Aware AI Smart Classroom" [1] study suggests a real-time feedback system that makes use of multimodal sensing and deep learning. Technologies like as haptic gloves, cameras, microphones, GPU clusters, and mobile cloud computing are used for processing data in real-time. Algorithms for crowd score quantification, behavior analysis, and emotion identification including open SMILE, DRMF, CERT, Caffe, and Nvidia DIGITS all use deep neural networks. Results and accuracy are not especially measured because the method is conceptual in nature and its suitability can be verified using a SUNYAlbany template classroom. The failure of achieving performance in real time The disadvantages include quantifying subjective human inputs, combining technology, and requiring an acceleration of two to three orders of magnitude. Futuristic elements include things like real time audience score aggregation, customized feedback based on cognitive load assessment, and possible uses outside education. (for instance, instruction, medical care). Future research suggests using eye-tracking for feedback engagement, physiological sensors for mood control, and distributed smartphone networks for pre computations to develop scalable, adaptive AI-driven educational systems.

AI methods in smart classrooms, examining 39 [2] publications between 2018 and 2023. Findings and Precision: Though few make it to TRL 5-7 (classroom-tested), the majority of ideas are at TRL 3-4 (lab validated proofs of concept); none reach TRL 8-9 (totally operational). The data is collected by Learning Systems, sensors, cameras, and IoT. Six publications use sensor data, while 28 publications use image/video data. The most common algorithms, with 28 publications, are data mining, ANNs [5], SVM, KNN, and CNNs. The focus on young adults, limitations in the real world, and neglect to include primary and secondary schools, the lack of consideration for safety and privacy, and how it affects learning-only three publications discuss Limitations include development, learning, and more. The role of AI in online education is carefully mapped out.

[3] in this research through an analysis of 35 articles. Accuracy/Results: DL models such as DBN-ELM attained 97%, RF 77%, and SVM up to 89%. The technologies utilized include social media sites like Facebook and Twitter, MOOCs, Google Forms, and Kaggle datasets. Deep Learning (DL) comprises ANN, RNN, and DBN, whereas Machine Learning (ML) predominates (65%) with Decision Trees (DT), Random Forest (RF), and SVM being the most popular algorithms. DL potential is underutilized, dataset sizes are small, standardized data is lacking, dynamic student performance is overlooked, and class imbalance problems are not addressed. Futuristic Aspects: The study emphasizes larger, standardized datasets and temporal data integration for better predictor performance. It suggests ensemble approaches for dynamic performance prediction, real-time interventions, and increased feature engineering to improve educational outcomes.

[5] Data, Adaptive Learning, Adaptable Learning, Recommendation, and Content Delivery are the five modules of the framework that Murtaza et al. AI-based personalized e-learning systems. Findings measures are not provided, learner performance prediction is enhanced by models such as Bayesian Knowledge Tracing (BKT) and Deep Knowledge Tracing (DKT). Utilizing datasets from learner interactions and assessments, the technologies utilized included knowledgetracing, machine learning (ML), deep learning (DL), and recommender systems. BKT, DKT (using RNN, LSTM, and GRU), Decision Trees, kNN, ANN, Item Response Theory (IRT), Learning Factor Analysis (LFA), and clustering methods like K means are some of the algorithms that are employed. Cons: Among the challenges are identifying features, developing adaptable content, properly monitoring knowledge, carrying out ongoing assessments, and modifying student preferences. Predictions for the Future: The proposed framework integrates real-time recommendations, continuous assessments, and flexible and adaptable learning for dynamic, personalized education. Future advancements will focus on better learner preference modeling, scalable content production, and advanced feature engineering.

[4] An intelligent tailored e-learning system that uses the Takagi-Sugeno Fuzzy Inference System (TSFIS) to identify learner frustration and provides gain-frame motivational messages based on regulatory fit theory is presented in the paper by Karthika et al. (2023). Algorithms and Technologies: It is written in Python and employs exploratory factor analysis (EFA) for feature grouping, Moodle LMS for behavioral data collecting, and TSFIS for emotion prediction. Results and Precision: In tests conducted on 43 undergraduate students, the experimental group did significantly better on tests ($p=0.019$) and had a higher emotional quotient ($p=0.003358$) than the control group. The system is specifically aimed at dealing with frustration, samples a small number, limits students to one course, and does not consider learning style. Future directions include investigating more emotions, scaling up to larger populations, and integration into more complete-featured learning systems for more personalized instruction.

[6] The Evolving Hypergraph Manta ray Foraging Convolution Neural Network (EHMFCNN) is used in the study by Patil and Shirgave (2025) to improve the delivery of video lectures by introducing a teacher emotion recognition system. Algorithms and Technologies: It is implemented in Python and employs EHMFCNN with Manta Ray Foraging (MF) optimization for emotion recognition, Fast Discrete Curvelet Transform with Wrapping (FDCT-WRP) for feature extraction, and Dense Residual Dualshuffle Attention Network (DRDA Net) for frame classification. Findings and Precision: It demonstrated 97.5% accuracy, 98% precision, 97.8% recall, and 98.2% F1-score for emotions when tested on the NPTEL-Indian English speech dataset. Cons: Currently only available on YouTube video frameworks, the system suffers from occlusion circumstances, which restricts performance when facial characteristics are hidden. Futuristic Aspects: It provides instructors with real-time feedback, intends to interface with mobile apps for real-time

emotion recognition in the classroom, and seeks to implement cutting-edge algorithms for increased scalability and adaptability across various educational platforms.

III. PROPOSED MODEL METHODOLOGY

The proposed Smart Education Platform is an advanced system that designed to deliver adaptive, emotionally intelligent learning experiences by continuously analyzing students' emotions and tailoring content in real time. Central to the model, there is a multimodal emotion recognition pipeline that ingests three principal types of User data includes facial expressions via webcam and responses to brief contextual surveys. These sources are processed using deep learning models such as ResNet for visual analysis, modality-specific features representing the learner's affective state. The system then employs an information fusion technique after feature extraction from each modality, unified emotional profile of the user. Early-stage fusion allows the platform to capture cross-modal interactions, hence improving recognition accuracy for complex emotional states, such as engagement, confusion, or annoyance. These fused features are passed to a classification module, which is often a deep neural network or recurrent layer, like LSTM, which outputs a real-time emotion label. The emotion classification acts as a continuous feedback signal for a reinforcement learning agent that Orchestrates content delivery. Emotional states are seen as part of the environment by the RL agent, which chooses interventions to maximize student engagement and learning outcomes. Examples of accommodations include advancing to the next video or quiz, providing condensed materials or additional support, all chosen to re-engage the learner or address negative emotions. The agent is guided by a reward function that increments for detected engagement (+1) and decrements for signs of disengagement or frustration (-1), allowing for policy optimization over time. A critical aspect of the proposed architecture is its seamless integration with existing e-learning systems such as Moodle via a Flask-based web application. This ensures that adaptive interventions can be provided without disrupting established educational workflows. Privacy and ethical data usage are foundational to the system's design. Users retain control through features like webcam opt-out, informed consent mechanisms, and on-device processing options, which minimize invasive data handling and foster trust. The model is rigorously trained on large-scale emotion datasets (such as AffectNet), and validated using cross-validation techniques to ensure robustness across different demographics and learning contexts. The empirical results show that combining visual and acoustic modalities with contextual input outperforms unimodal approaches, yielding higher accuracy and F1 scores for emotion prediction. By unifying state-of-the-art multimodal sensing, deep learning for affect recognition, and adaptive RL-based content management, the proposed Smart

Education Platform transcends the limitations of static online learning. It creates a personalized, ethically-sound, and human centered environment that dynamically adapts to each learner's emotional journey, setting a strong foundation for the next generation of digital education systems.

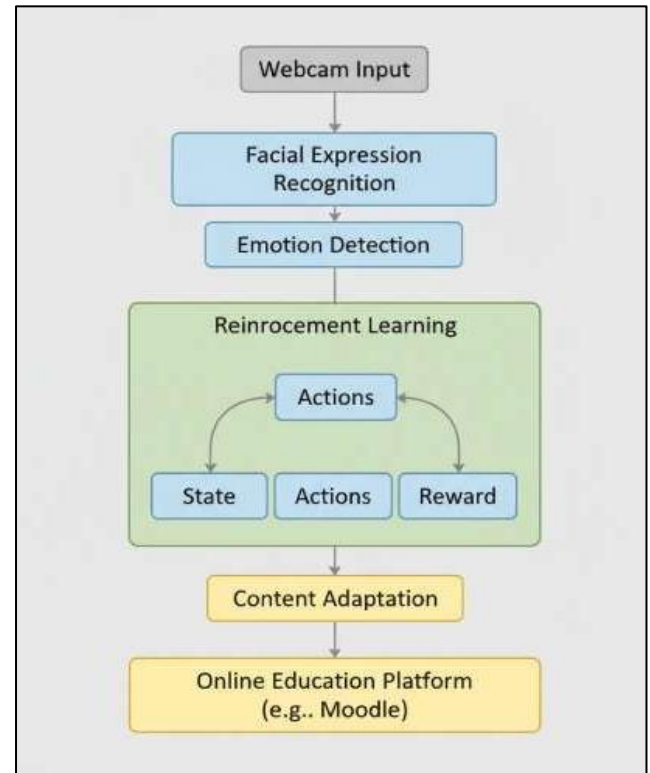


Fig 1 Block Diagram for Proposed Model

IV. RESULT AND DISCUSSION

The proposed system is designed and implemented as follows:

➤ Course Dashboard with Emotion Analytics

Above image displays the main Course Dashboard of the Smart Education Platform. This is the central hub where the user can view their overall progress and engagement.

Course Aggregation: The dashboard shows that the user is enrolled in multiple courses ("Python Programming," "Java Object-Oriented Programming," "Web Development with JavaScript"), demonstrating the platform's ability to manage a diverse curriculum. **Progress Tracking:** Metrics such as "Videos Completed," "Total Watch Time," and "Avg Quiz Score" provide a quantitative overview of the user's learning journey. Currently, these are at zero, indicating a new user session.

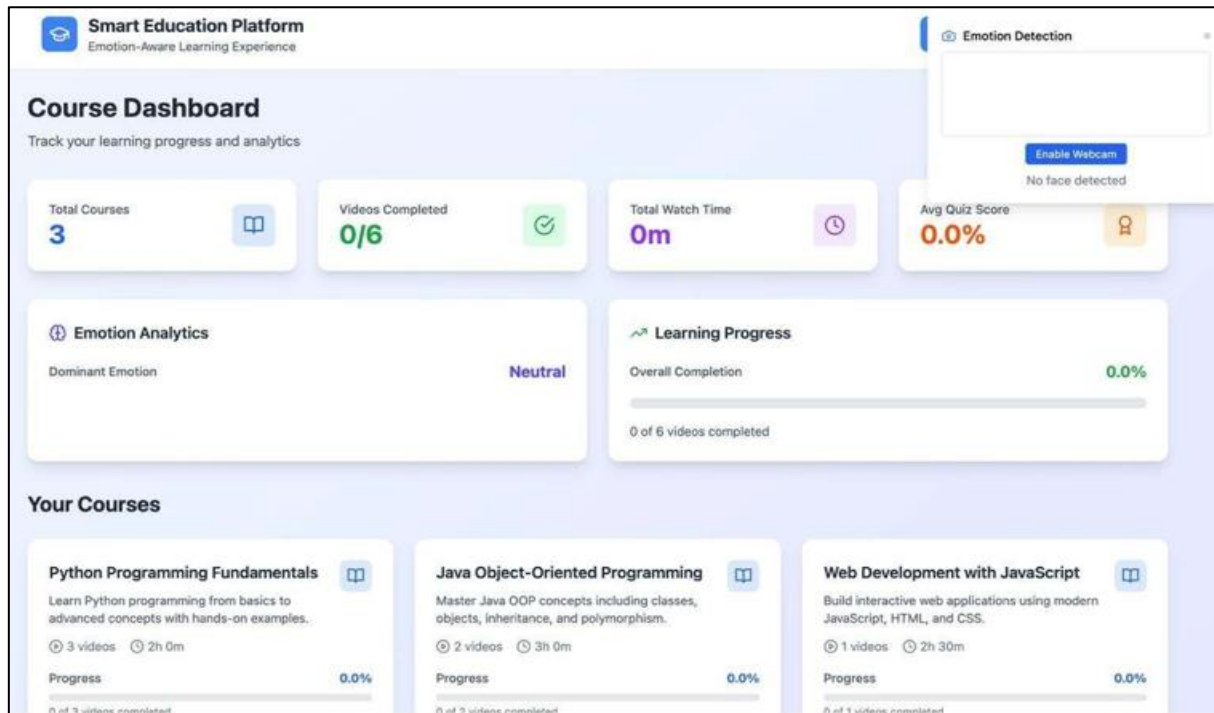


Fig 2 Course Dashboard with Emotion Analytics

➤ *Real-Time Emotion Detection and System Intervention*

This image captures a critical moment of intervention by the platform.

• *Detecting Confusion:-*

✓ Emotion Detection: The system, via the webcam feed, has

detected that the user's facial expression signifies "Confused" with a high confidence of 79.6%.

✓ Contextual Trigger: This detection occurred while the user was watching a video lesson on "Classes and Objects" in the Java course.

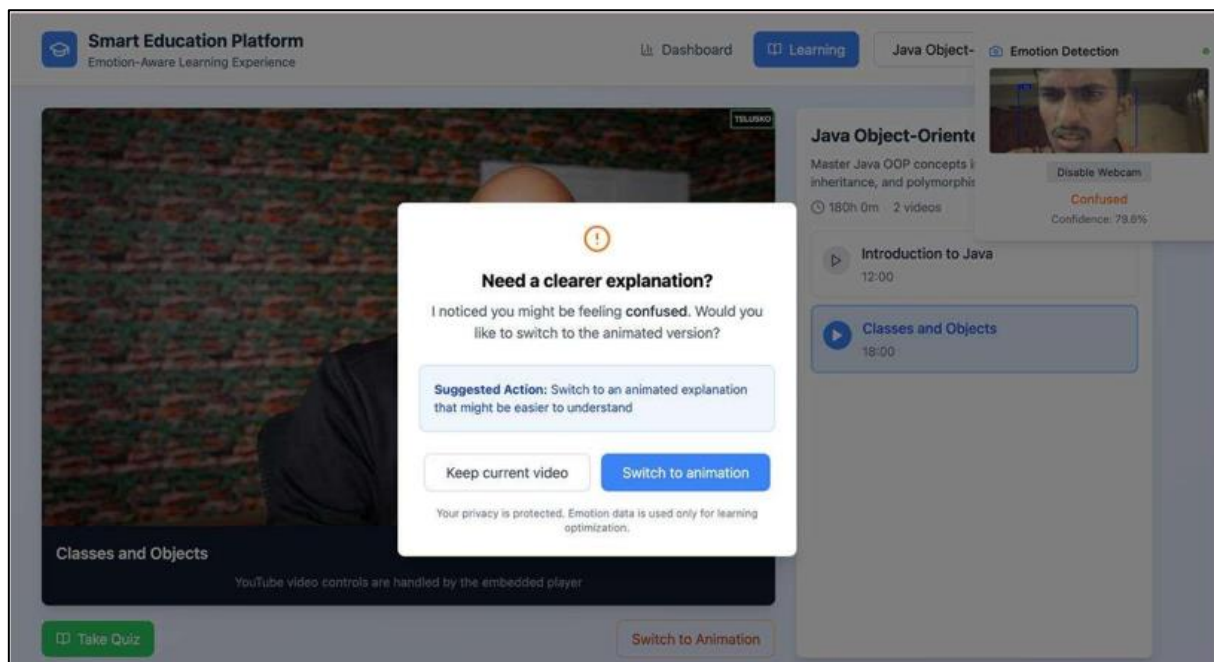


Fig 3 Detecting Confusion

• *Detecting Angry:-*

This image showcases a different scenario of system intervention.

✓ Emotion Detection: Here, the model has identified the user's emotion as "Angry" with a very high confidence of 99.6%.

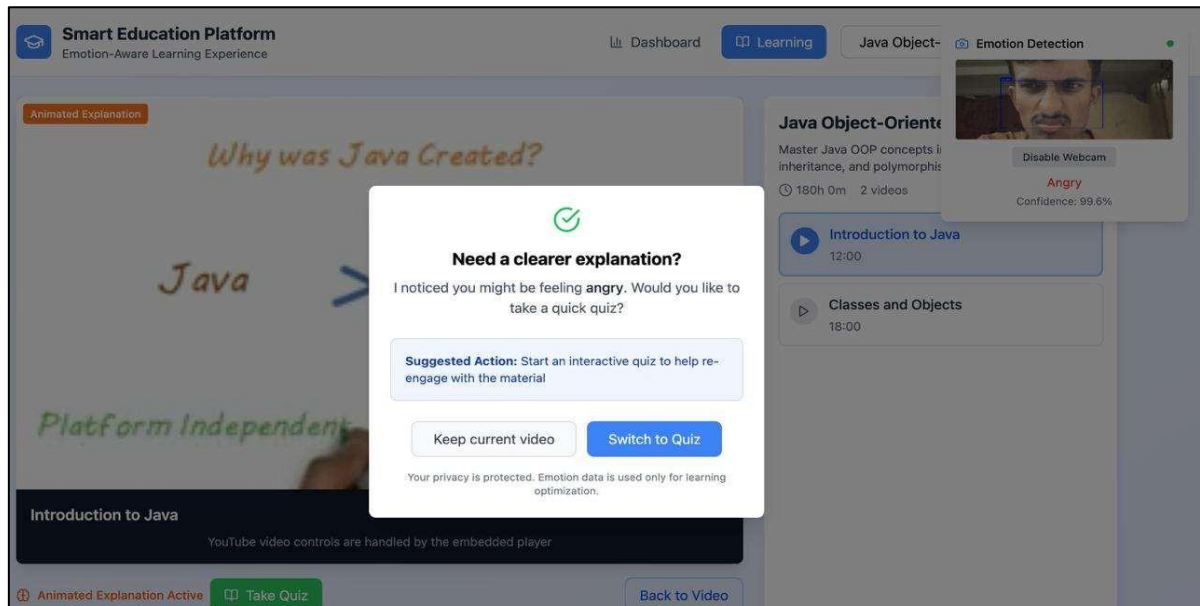


Fig 4 Detecting Angry

➤ Interactive Quiz Component Taking the Quiz

This image shows the Interactive Quiz interface. This is one of the adaptive actions the system can suggest. Here, the

user is presented with a multiple-choice question, "What does JVM stand for?". The interface is clean and straightforward, allowing the user to select an answer and proceed.

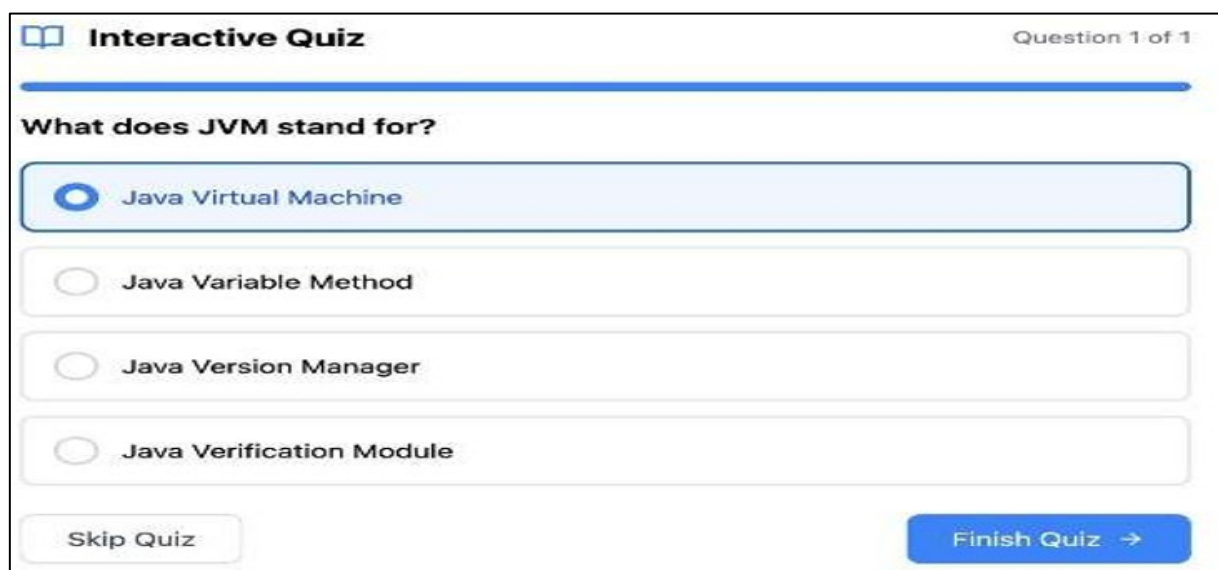


Fig 5 Taking the Quiz

• Quiz Completion

This image confirms the successful completion of the quiz, showing that the user "scored 100%

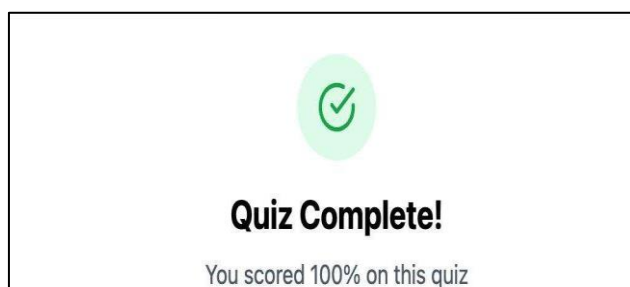


Fig 6 Quiz Completion

➤ Graphical Representation

• Angry Emotion Confidence Over Time

This graph shows the confidence level for the "Angry" emotion. The confidence starts at a baseline of 50% and gradually increases, peaking at 65.3% around the 5-minute mark. The slight dip before the final peak could represent a momentary change in expression before the feeling of frustration becomes more pronounced.

• Confused Emotion Confidence Over Time

The confidence for the "Confused" emotion follows a more rapid upward trajectory, starting at 60% and quickly climbing to a peak of 85.6%. This sharp increase suggests a

specific event during the learning session, likely the introduction of a difficult concept, caused a sudden spike in confusion. The minor dip towards the end might indicate a brief moment of re-engagement before the confusion solidifies.

- *Neutral Emotion Confidence Over Time*

This graph illustrates the confidence level for the

"Neutral" emotion, which acts as the baseline affective state. It begins at a very high confidence of 90% and climbs to a near-certain 99.9%. This indicates that when the user is not exhibiting strong emotions, the model is extremely confident in identifying this neutral state.

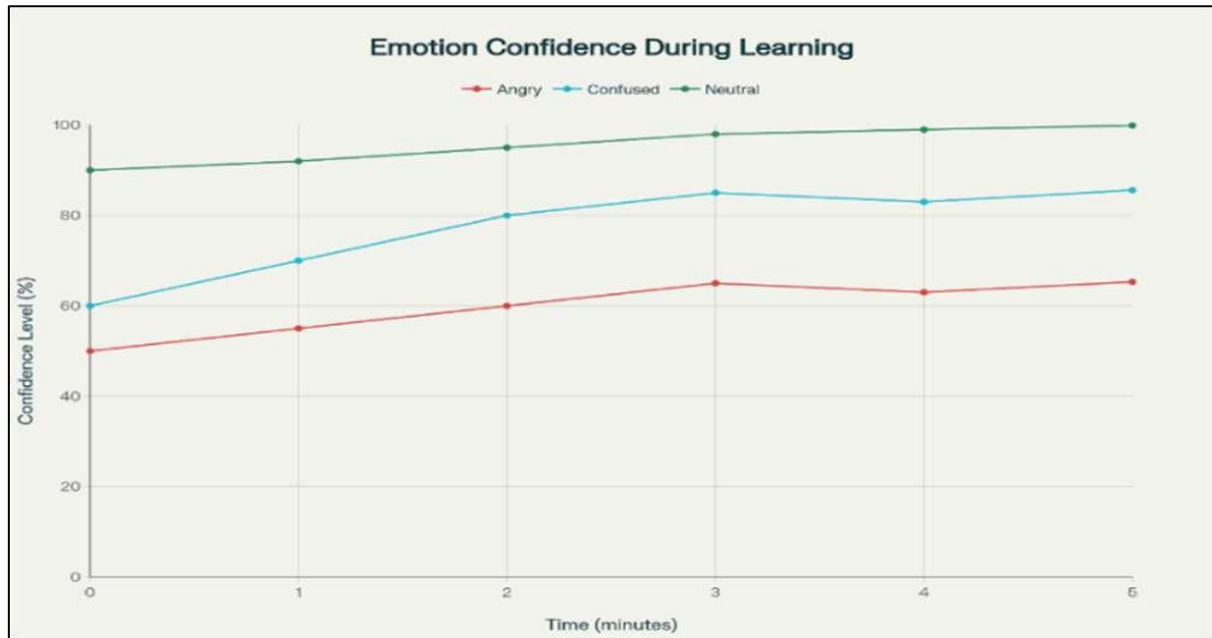


Fig 7 Line graphs of Angry, Confused, and Neutral emotion confidence levels over time.

V. CONCLUSION

An innovative approach to personalized instruction is provided by the Smart Education Platform, which uses machine learning (ML) to deliver emotion-based content. The platform uses machine learning techniques like CNNs and LSTMs to reliably identify a student's emotional state by utilizing real-time emotion identification from inputs including webcams, microphones, and physiological sensors. The decision engine may dynamically modify instructional content by modifying its difficulty, style, and interaction to suit the emotional and cognitive needs of the learner thanks to this emotional data and the student's learning profile. By improving the emotion detection models and updating the student's profile, the closed feedback loop guarantees ongoing progress and gradually increases accuracy. In the end, this system optimizes learning outcomes, increases engagement, and promotes emotional well-being by customizing instruction to each person's emotional context, showcasing the ability of machine learning to produce flexible, student-centered learning environments.

FUTURE SCOPE

The future scope of this Smart Education Platform lies in expanding its multimodal emotion detection by integrating additional data sources such as voice, biometric feedback, and keystroke patterns, providing even more accurate emotional insights and personalized learning experiences.

Advanced reinforcement learning agents will be developed to adapt content not only at a lesson level but also within activities, adjusting difficulty and delivery style based on real-time emotion and engagement shifts. Integration with popular Learning Management Systems like Moodle will broaden its reach, while instructor dashboards can offer real-time classwide emotion analytics to help educators improve teaching strategy. Scalability will be achieved through cloud deployment and mobile accessibility, making adaptive, emotionally aware education possible in diverse global contexts. Emphasis on privacy and ethical AI will remain paramount, including transparent consent controls and bias mitigation strategies, ensuring trustworthy deployment. Combined, these advances will transform digital learning into a proactive, responsive, and human-centered ecosystem.

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