Emotion-Aware Adaptive Quiz System: Enhancing Learning Through Real-Time Emotion Detection

I. ABSTRACT

This paper introduces an emotion-aware e-learning platform that adjusts quiz difficulty based on real-time emotion detection to improve learner engagement and performance. While traditional e-learning methods lack emotional context, this system integrates emotion recognition to provide personalized learning experiences. Using facial expression recognition through a Convolutional Neural Network (CNN), the platform categorizes emotions into seven types: Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral. The system adapts quiz difficulty based on these emotions—challenging questions for positive emotions and easier ones for negative emotions. Built with Flask for the backend and OpenCV for emotion detection, the system demonstrated successful real-time adaptations during user testing. Results showed that users in positive emotional states performed better on difficult questions. The emotion detection model achieved 91.23% accuracy with a 23ms detection time. This approach highlights the potential for emotion-based feedback to enhance e-learning systems. Future work could explore integrating machine learning models to further optimize difficulty levels based on emotional and performance data in real time.

Keywords- Emotion-aware e-learning, Real-time emotion detection, Convolutional Neural Network (CNN), Personalized learning, Facial expression recognition, Emotion-based difficulty adjustment, Flask, OpenCV, User engagement, Machine learning models

II. INTRODUCTION

E-learning platforms have revolutionized education by providing accessible and flexible learning opportunities. However, most current systems lack the ability to adapt to learners' emotional states, which play a crucial role in the learning process. Emotions such as frustration, boredom, or excitement can significantly impact a student's ability to absorb and retain information. This gap in personalization presents an opportunity to enhance the effectiveness of e-learning experiences.
Our project introduces an emotion-aware e-learning platform that integrates real-time emotion detection with adaptive quiz difficulty. By leveraging computer vision and machine learning techniques, the system captures and analyzes learners' facial expressions during quiz sessions. We use a pre-trained convolutional neural network model that classifies emotions into seven categories: Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral. This emotional feedback is then used to dynamically adjust the difficulty of subsequent questions, creating a more engaging and responsive learning environment. These emotions/data work for our problem because this is meant for an E-learning platform and a testing one. Because emotions would be more stringent in that scenario.

The core of our innovation lies in the seamless integration of:

1. Real-time emotion detection using a CNN trained on facial expressions commonly observed during studying,

with emotion capture occurring every second.

2. A dynamic difficulty adjustment algorithm that considers the detected emotion and user performance. For instance, happy emotions lead to harder questions, while fear, disgust, anger, or sadness result in easier questions.
3. An adaptive quiz system focusing on machine learning concepts, with questions ranging from easy to hard difficulty levels.
4. A comprehensive dashboard for tracking user statistics and emotional patterns throughout the learning process, including emotion distribution, question difficulty distribution, and overall performance charts.

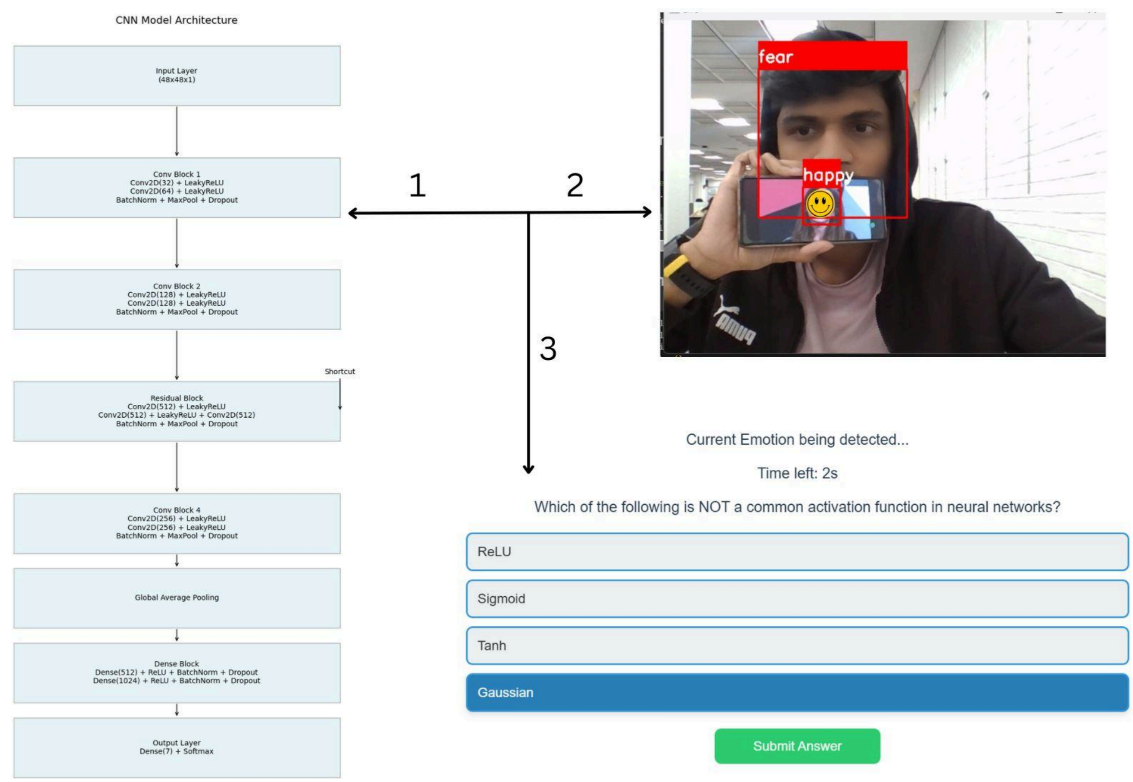

Fig 1: Fast and Accurate Emotion Detection with Advanced CNN and Residuals for Real-Time Quiz Systems

This emotion-aware approach enhances traditional adaptive learning systems by integrating effective computing principles. Tailoring content delivery to learners' emotional responses creates a more empathetic and effective digital learning experience.Implemented with Flask for the backend and JavaScript for the frontend, the system integrates webcam capture and real-time client-server communication, enabling seamless emotion detection and quiz adaptation. Preliminary results show improved engagement and learning outcomes, offering a personalized experience. The system balances challenge and support based on emotional feedback, paving the way for advancements in educational psychology and adaptive learning.

III. RELATED WORK

1. Paperswithcode (2024)[1] proposed an innovative pipeline for analyzing student behavior in online learning environments. Their approach utilized facial video processing with a single neural network, pre-trained on face identification and fine-tuned for facial expression recognition. This model demonstrated the capability to predict engagement levels, individual emotions, and group-level affect in real-time, even on mobile devices.
Drawbacks- The study's focus on facial expressions alone may have overlooked other important emotional cues, potentially limiting its comprehensive understanding of learner emotions.

2. A systematic review by NCBI (2024)[2] provided a broader perspective on AI-driven emotion assessment in educational settings. The review explored various AI approaches, including machine learning and facial recognition techniques. Notably, it identified emerging factors such as federated learning, CNNs, RNNs, and ethical considerations in AI development.
Drawbacks- While comprehensive, this review highlighted the need for further investigation into the relationships and implications of these emerging factors, suggesting a gap in our understanding of how these technologies interact and impact learning outcomes.

3. IJRITCC (2024) introduced the Intelligent Multimodal Emotion Recognition System (IMERS)[3], which took a more holistic approach to emotion recognition in e-learning. IMERS incorporated facial expressions, voice, and text analysis, addressing the limitations of single-modality systems. By using multimodal fusion, IMERS aimed to provide a more comprehensive understanding of emotions.
Drawbacks- However, the study did not explore real-time processing capabilities or integration with adaptive quiz systems, leaving room for further development in these areas.

Our work enhances previous studies by:

1. Integrating real-time emotion detection with adaptive quizzes for immediate personalization.
2. Using emotional data to tailor learning experiences.
3. Employing a pre-trained CNN model for improved accuracy in learning contexts.
4. Implementing a dashboard for tracking emotions and performance, offering valuable insights to educators.

IV. TECHNICAL MEAT

1. System Architecture:

The emotion-aware e-learning platform consists of two main components:

1. Backend:

- Flask-based server implemented in Python.
- Handles emotion detection using a pre-trained CNN model.
- Manages quiz questions and adapts difficulty based on detected emotions.
- Processes user answers and updates user statistics.

2. Frontend:

- A web interface developed using HTML, CSS, and JavaScript.

- Captures webcam feed for real-time emotion detection.
- Displays quiz questions and options, providing an interactive user experience.
- Features a performance dashboard with charts for real-time feedback.

Key Features:

- Real-time Communication: The frontend and backend communicate asynchronously through AJAX requests.
- Emotion Detection: OpenCV is integrated for face detection in captured webcam images.
- Data Visualization: The system employs Chart.js for creating interactive visualizations on the dashboard.
- Modular Design: The architecture is designed to be modular, allowing for the easy extension of quiz questions and emotion detection capabilities.

The platform operates on a client-server model, where the client (browser) continuously sends webcam images to the server for emotion detection. The server then responds with the detected emotion and selects appropriate quiz questions. This architecture enables efficient processing and real-time adaptation of the quiz based on the user's emotional state. The emotion detection system uses a custom Convolutional Neural Network (CNN) trained on the FER (Facial Expression Recognition) dataset[4], classifying facial expressions into the seven categories:

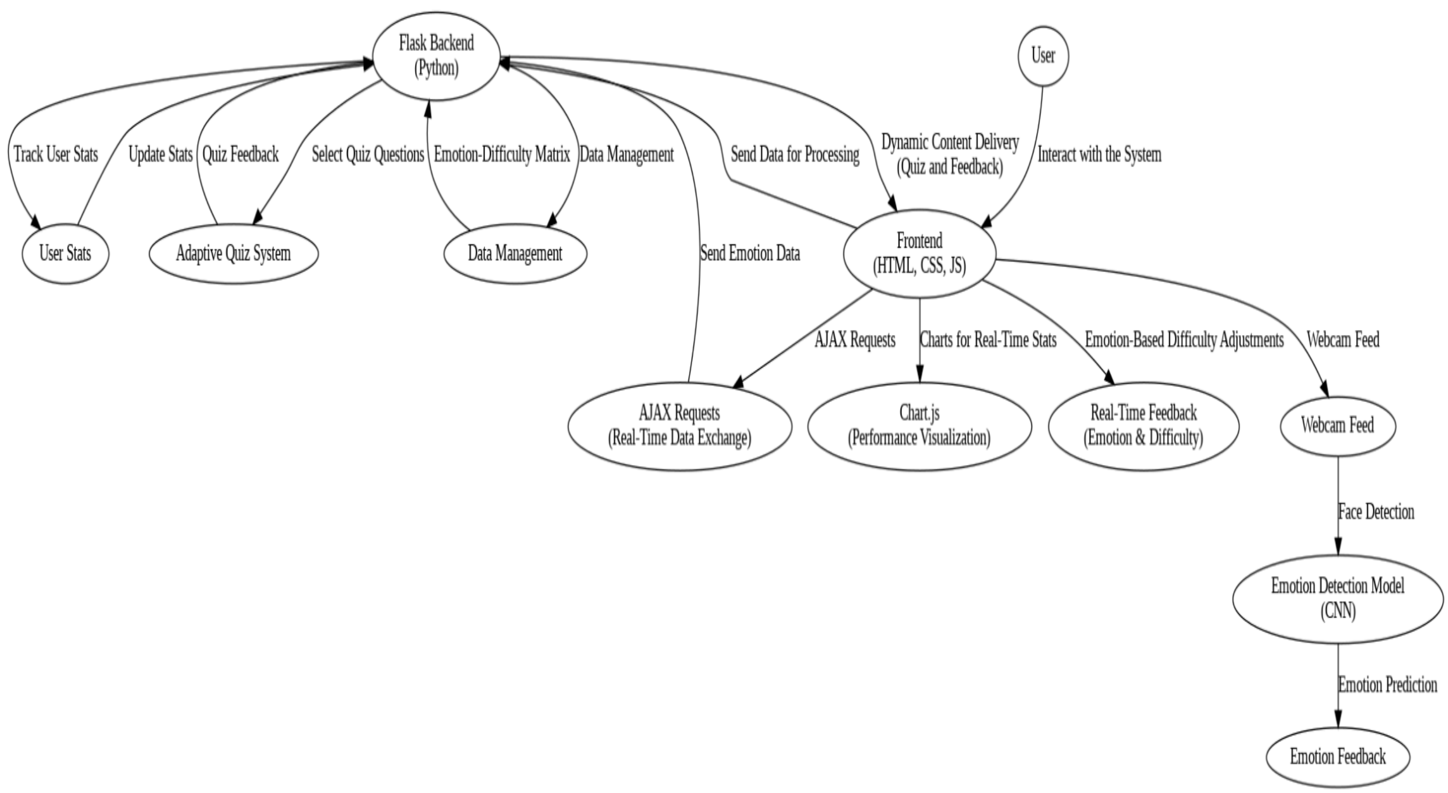

Fig 2. Model FLow Diagram for the Emotion Aware E Learning Platform

2. Model Architecture:

The emotion detection system leverages a Convolutional Neural Network (CNN) designed to capture key facial features and classify emotions from webcam images. Below are the core components of the model architecture:

Input Layer: The model accepts grayscale images of size 48x48 pixels with a single channel.

Convolutional Layers: The first layer consists of a 3x3 convolutional filter with 32 filters, followed by a LeakyReLU activation to prevent the "dying ReLU" problem. The second convolutional layer increases the number of filters to 64, followed by another LeakyReLU activation. Batch normalization is applied after these layers to stabilize learning, and max pooling is used to reduce spatial dimensions. A dropout rate of 0.3 is used after each convolutional block to mitigate overfitting.

Second Block: The second block consists of two convolutional layers with 128 filters each, followed by LeakyReLU activations, batch normalization, and max pooling with dropout for regularization.

Third Block with Residual Connection: The third block includes two convolutional layers with 512 filters, utilizing the LeakyReLU activation and batch normalization. A residual connection is introduced here: the output of the third block is added to the shortcut connection from earlier in the network to facilitate better gradient flow and prevent vanishing gradients. A 1x1 convolution is used to match the shapes of the output and shortcut connections.

Fourth Block: This block includes two convolutional layers with 256 filters, followed by LeakyReLU activations, batch normalization, max pooling, and dropout.

The model utilizes Global Average Pooling (GAP) instead of flattening to reduce the number of parameters and enhance generalization by averaging feature maps across spatial dimensions. Following the pooling layer, two fully connected (dense) layers with 512 and 1024 units are used, each followed by batch normalization and dropout (0.4) for regularization. The output layer consists of 7 units corresponding to the 7 emotion categories: Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral, with a softmax activation function to output probabilities for each emotion class. To prevent overfitting, L2 regularization is applied to both the convolutional and fully connected layers, penalizing large weights.

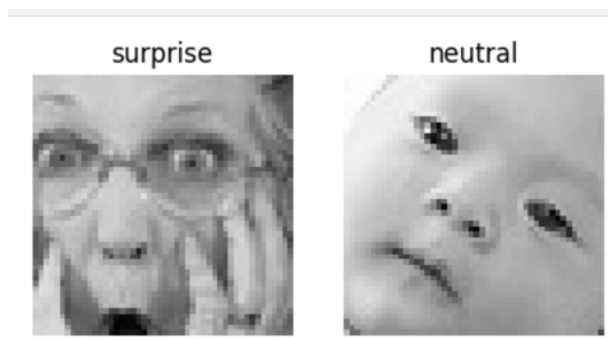

Fig 3: Visualizing the FER Dataset[4]

Real-Time Processing-
The emotion detection process occurs in real-time during quiz sessions:

OpenCV's Haar Cascade Classifier detects faces in the webcam frames. Detected faces are converted to grayscale, resized to 48x48 pixels, and normalized before being fed into the CNN model. The preprocessed face image is passed through the CNN model for emotion prediction. The detected emotions influence the quiz difficulty. For example, 'Happy' emotions trigger more challenging questions, while 'Fear', 'Disgust', 'Angry', or 'Sad' emotions result in easier questions. This architecture allows for dynamic, personalized learning experiences by adapting quiz difficulty based on the learner's emotional state in real-time.

<u>3. Adaptive Quiz System:</u>

The Adaptive Quiz System is a core component of our emotion-aware e-learning platform, designed to dynamically adjust question difficulty based on the learner's emotional state and performance. This system ensures a personalized and engaging learning experience.

Question Pool-

The quiz system utilizes a diverse pool of 75 machine learning-related questions, categorized into three difficulty levels:

1. Easy: Basic concepts and definitions
2. Medium: Intermediate topics and applications
3. Hard: Advanced techniques and complex problem-solving

Each question includes an ID, text, multiple-choice options, correct answer, and difficulty level.

Difficulty Adjustment Algorithm-

The system employs a sophisticated algorithm to determine the difficulty of the next question:

1. Emotion-based Adjustment: If the detected emotion is 'Happy', the difficulty is set to 'hard'. If the emotion is 'Fear', 'Disgust', 'Angry', or 'Sad', the difficulty is set to 'easy'. For 'Surprise' or 'Neutral' emotions, the algorithm considers additional factors. An instance of the algorithm can be seen in Fig 4 which demonstrates the decision making process of the algorithm.
2. Performance-based Adjustment: The system tracks consecutive correct answers. For 'Surprise' or 'Neutral' emotions:If the emotion is the same as the previous question and the user has answered correctly twice in a row, the difficulty is increased to 'hard'. If the current emotion differs from the previous one, the difficulty remains unchanged.

Algorithm 1 Emotion Detection Difficulty Adjustment

```
procedure ADJUSTDIFFICULTY(UserStats, Emotion, CurrentDifficulty)
    if not IsValidEmotion(Emotion) then
        return CurrentDifficulty
    end if
    if Emotion = Happy then
        difficulty ← Hard
    else if Emotion ∈ {Fear, Disgust, Angry, Sad} then
        difficulty ← Easy
    else if Emotion ∈ {Surprise, Neutral} then
        if LastEmotion = Emotion then
            if ConsecutiveCorrect ≥ 2 then
                difficulty ← Hard
            else
                difficulty ← Easy
            end if
        else
            difficulty ← CurrentDifficulty
        end if
    end if
    if Random() ¡ RandomProbability then
        difficulty ← Hard
    end if
    questions ← SelectSuitableQuestions(difficulty)
    if questions.isEmpty() then
        questions ← AllQuestions
    end if
    UpdateUserStats(UserStats, Emotion, difficulty)
    return difficulty, questions
end procedure
```

Fig 4: The Proposed algorithm to decide difficulty

Question Selection Process-

1. The system receives the current emotion, previous difficulty level, consecutive

correct answers, and last detected emotion.

2. It applies the difficulty adjustment algorithm to determine the new difficulty level.
3. A question is randomly selected from the pool of questions matching the new difficulty level.
4. If no matching questions are found, a question is randomly selected from the entire pool.

Performance Tracking-

The system maintains detailed statistics:

- Total questions answered
- Number of correct answers
- Emotion counts throughout the quiz
- Difficulty level distribution of questions asked
- An emotion-difficulty matrix to track correlations between emotions and question difficulties

This adaptive approach ensures that the quiz remains challenging yet achievable, adjusting in real-time to the learner's emotional state and performance. By doing so, it aims to maintain engagement and optimize the learning experience for each individual user.

4. Supplementary Features:

To enhance usability and robustness, the platform offers several supplementary features. The user interface provides real-time emotion feedback during the quiz, multiple-choice question formats with a dynamic submit button, and a timer to ensure timely responses. The performance dashboard uses pie charts to display emotion distribution, bar charts for question difficulty levels, and doughnut charts for overall performance. Emotion processing aggregates emotions over the duration of each question to determine the dominant emotion, enabling adaptive adjustments. Data management employs efficient structures to track emotion counts and maintain an emotion-difficulty matrix, ensuring real-time adaptability. Robust error handling includes fallback mechanisms for undetected faces or unrecognized emotions, preserving the continuity of the quiz experience.

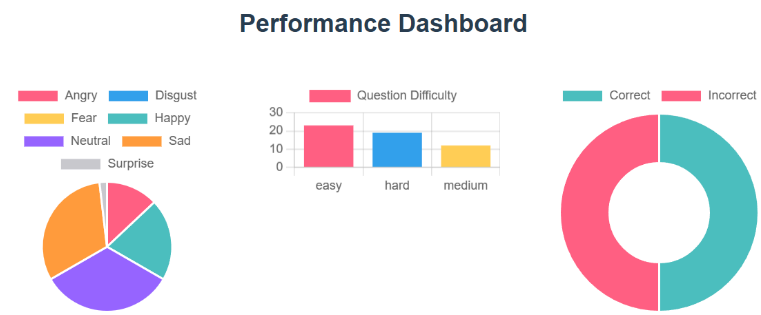

Fig 5: Dashboard of an User 1

V. VALIDATION

Proposed User Study-

Objective: Evaluate the effectiveness, usability, and emotional engagement of the emotion-aware e-learning system, focusing on- Real-time emotion detection and difficulty adaptation and User experience and system interaction.

Target Group: 100 Students (16-30 years) familiar with e-learning platforms.
Demographics: Mix of genders and diverse backgrounds depending on quiz content.

Methodology:

Pre-Test Questionnaire- Record the user's current emotional state/mood (using a scale or short questions). Inquire about the participant's background in the quiz domain (e.g., knowledge level in the subject).

System Interaction- Participants take a quiz with emotion-based difficulty adjustments (e.g., happier users get tougher questions).

Conduct a randomized test with unrepeated questions, ensuring the same difficulty level but different order to test the system's robustness.

Post Test Survey- Collect feedback on usability, emotional engagement, and the effectiveness of difficulty adjustments.

Hypothesis testing- Use t-test statistics to test if the quiz score is related to emotions.

Usability Heuristics Evaluation:

1. Visibility of System Status- Ensure users are aware of emotion detection and quiz adjustments.
2. Match Between System and the Real World- Feedback should feel intuitive and natural.
3. User Control and Freedom: Allow participants to skip questions or override difficulty adjustments.
4. Consistency and Standards: Ensure emotion detection and difficulty changes are consistent across quizzes.
5. Error Prevention and Flexibility: Avoid misinterpreting emotions and provide easy fixes.
6. Aesthetic Design: Keep the interface clean, clear, and minimal.

Metrics:

Emotion Detection Accuracy: Evaluate how well the system detects emotions.

User Engagement Track interaction time and quiz attempts.

Quiz Performance: Measure how emotion-based adjustments impact performance.

User Satisfaction: Collect feedback on the interface, emotional feedback, and perceived learning improvement.

Learning Outcomes: Assess if emotional adjustments help improve task performance, especially in more difficult questions for happier users.

Validation of Emotional Adjustments-

To validate the emotional-state-based difficulty adjustment, we will test the following:

Mood & Task Difficulty: Measure if users in a positive mood perform better on difficult questions and if frustrated users perform better on easier ones.

Mood Impact Over Time: Test if users in a good mood continue to perform well on tough questions in later rounds.

Emotional Feedback: Track if improvements in quiz performance boost user mood, creating a positive feedback loop.

Motivation & Engagement: Survey users to assess if emotional adjustments enhance motivation and engagement.

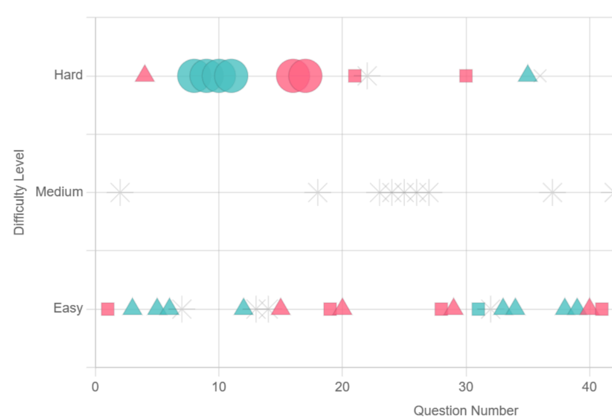

Fig 6: User 1 Performance Scatter Plot

The emotion-aware e-learning system was tested with two users of different backgrounds - one with ML knowledge and another with quiz domain expertise. The results showed distinct patterns in their learning experiences. The first user exhibited predominantly neutral emotions with periods of sadness and anger, struggled with performance (around 50% correct answers) as seen in Fig 5 and Table 1, and showed consistent engagement across medium difficulty questions but struggled with hard ones. In contrast, the second user demonstrated a more balanced emotional state (even distribution between happy, neutral, and sad emotions), achieved better performance (approximately 70% correct answers), and showed effective progression through difficulty levels. The system successfully adapted question difficulty based on both users' emotional states and performance, as evidenced by the scatter plots showing clear transitions between difficulty levels. The visualization of emotion-performance relationships through various charts (pie charts for emotions, bar charts for difficulty distribution, donut charts for performance, and scatter plots for temporal progression) effectively demonstrated how emotional states correlated with learning outcomes and system adaptability.

Positive Emotional State Example -
In the scatter plot in Fig 7 from the second user, there's a notable cluster of correct answers (turquoise circles) in the Hard difficulty level around questions 8-11. This coincides with a period where the pie chart shows significant Happy emotions, suggesting that positive emotional states enabled better performance even on difficult questions.

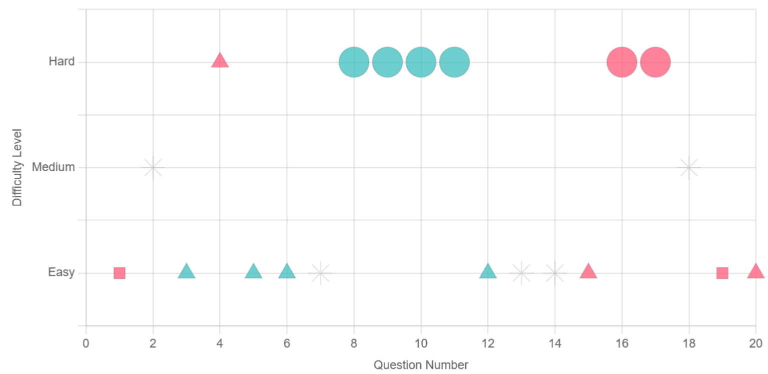

Fig 7: User 2 Performance Scatter Plot

Negative Emotional State Example -
In the first user's scatter plot Fig 6, despite having ML knowledge, there are instances of incorrect answers (pink triangles) for Easy difficulty questions around questions 20-30. This correlates with increased Sad and Angry emotions shown in the emotion distribution pie chart, indicating that negative emotional states impacted performance even on simpler questions. These patterns support the hypothesis that emotional state significantly influences learning performance, regardless of the user's domain knowledge.

User	Performance	Emotions		
		Happy	Sad	Neutral
User 1	0.5	21%%	32%	47%
User 2	0.75	31%	40%	29%

Table 1: Performance of the two test users

Model Performance Metrics-
Table 2 summarizes the key performance metrics of the emotion detection model, highlighting its accuracy and responsiveness.

Model Accuracy	91.23%
Emotion Detection Time	23ms
Frame Rate(prediction)	2 frame/sec

Table 2: Summarizing the ML performance

These metrics demonstrate the model's high accuracy and efficient performance, making it suitable for real-time applications in the quiz system.

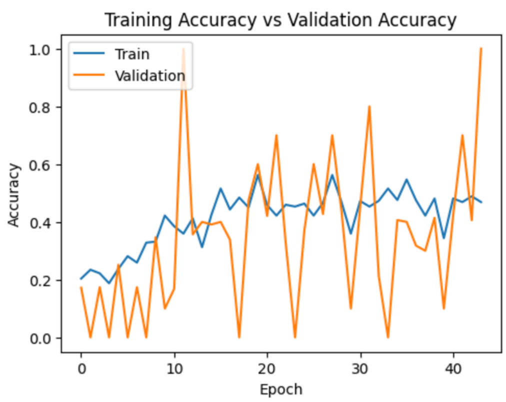

Fig 8: Model Accuracy

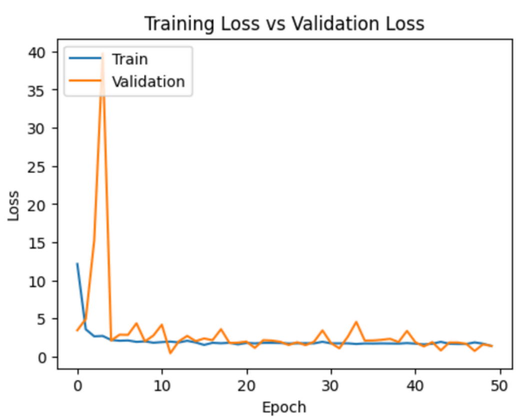

Fig. 9: Plotting Model Loss

Additionally the images have been tested at various light settings to make sure that the environment of the students won't be a factor causing errors in predictions.

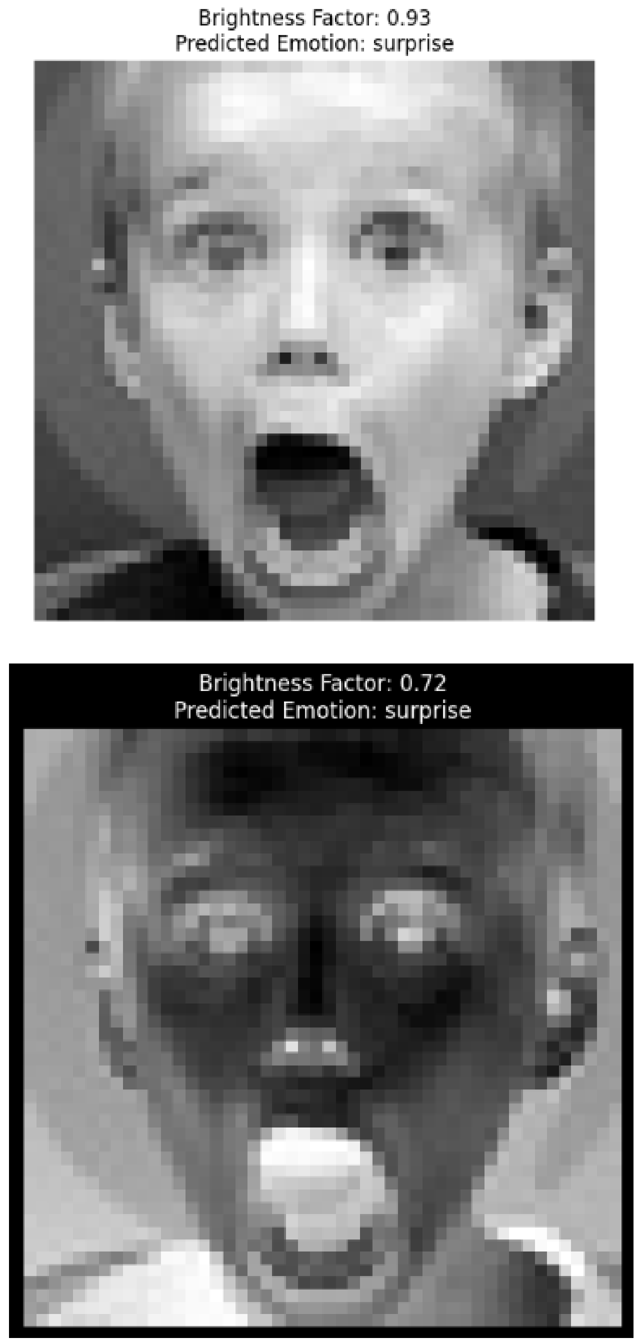

Fig 10: Comparing predictions at different intensities

__Key Challenges:__

The project faced several significant challenges in developing an emotion-aware e-learning platform. Real-time emotion detection required high accuracy and low latency to be effective during quiz sessions. Integrating this with dynamic quiz difficulty adjustment posed complex algorithmic challenges. Ensuring a seamless user experience while processing webcam data and adapting content in real-time was also demanding. Additionally, creating a robust system that could handle various lighting conditions and user behaviors while maintaining accuracy was a significant hurdle.

Innovative Solutions:
To address these challenges, the project implemented several innovative solutions. A custom CNN architecture with residual connections and global average pooling was developed, achieving 91.23% accuracy with a 23ms detection time. The system used an adaptive algorithm that considered both emotional state and consecutive correct answers to adjust quiz difficulty dynamically. Asynchronous communication between frontend and backend enabled smooth real-time updates. The platform also incorporated a comprehensive dashboard with real-time visualizations of emotion distribution, question difficulty, and performance, providing valuable insights into the learning process.

VI. FUTURE WORK

This project successfully explored the integration of emotion detection to dynamically adjust quiz difficulty, enhancing user engagement. The primary strength lies in the system's ability to personalize quiz difficulty based on real-time emotional states, leading to a more tailored learning experience. However, challenges remain in refining emotion detection accuracy and ensuring smooth real-time adjustments without lag. A key lesson from this project is the importance of balancing emotional feedback with cognitive load to avoid overwhelming users.

Future work could include integrating a machine learning model to predict the optimal difficulty level for each user based on historical performance and emotional cues, further improving system adaptability and user experience.

VII. CONCLUSION

This project demonstrates the potential of using emotion detection to adjust quiz difficulty in real-time, enhancing user engagement and performance. By tailoring the quiz experience to emotional states, we aim to optimize learning outcomes and improve motivation. The key takeaway is that emotional context plays a crucial role in user performance and can be leveraged to create more effective and personalized educational tools.

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