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# Emotion Aware Webpage Portfolio

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**Abstract:** The rapid evolution of user-centric design has led to the emergence of emotionally responsive digital interfaces. This project presents an Emotion-Aware Webpage Portfolio, a personalized web system that dynamically adapts its presentation based on the user's emotional state. Using real-time facial expression recognition powered by a browser-based machine learning model (TensorFlow.js), the system classifies emotions such as happiness, sadness, anger, surprise, and neutrality from live webcam input. These detected emotions are then mapped to adaptive UI components, enabling modifications in color themes, textual tone, animations, and interactive elements. The goal is to enhance user engagement by creating a portfolio interface that reacts intuitively to user affect. The project demonstrates that integrating affective computing with web technologies can significantly improve user experience, accessibility, and immersion. The results highlight strong potential for emotion-driven design in future web applications.

**Keywords:** Emotion detection, Affective computing, Web-based portfolio, Real-time facial expression recognition, TensorFlow.js, Adaptive user interface, Human–computer interaction, User experience personalization, Computer vision, Emotion-aware design

## I.INTRODUCTION

In modern web design, user experience has evolved far beyond static layouts and generic interactions. As digital interfaces increasingly seek to mirror human-like responsiveness, affective computing—the study of systems that can recognize, interpret, and respond to human emotions—has emerged as a transformative field. Traditional personal portfolios showcase skills, achievements, and identity, but they typically provide the same experience to every visitor regardless of their emotional context. This limitation reduces the depth of engagement and fails to leverage the potential of adaptive design.

This project addresses this gap by developing an Emotion-Aware Webpage Portfolio, a web interface capable of detecting user emotions and dynamically altering its presentation. Using real-time facial expression recognition through browser-based computer vision models such as TensorFlow.js, the system classifies emotions like happiness, sadness, anger, neutrality, and surprise. The detected emotional state then drives immediate UI adjustments—such as theme colors, typography, animations, and greeting messages—creating a personalized and immersive browsing experience.

The motivation behind this work is to explore how emotion-responsive interaction can enhance user engagement, improve accessibility, and offer a more human-centered web experience. By integrating affective computing principles into a functional portfolio, the project demonstrates a novel approach to interactive design. The outcome highlights the potential for emotion-driven interfaces to redefine the way users experience personal webpages and future web applications.

## II.LITERATURE REVIEW

The field of emotion-aware systems is rooted in affective computing, a term introduced by Picard (1997), which focuses on enabling machines to recognize and respond to human emotions. Affective computing has since expanded across domains such as human–computer interaction (HCI), behavioral analytics, and adaptive interfaces. Within this domain, facial expression recognition (FER) has become one of the most widely adopted methods for emotion detection due to its non-intrusive nature and ease of integration with digital systems.

Early FER systems relied on handcrafted features such as Local Binary Patterns (LBP), Gabor filters, and Histogram of Oriented Gradients (HOG). These techniques achieved moderate accuracy but struggled with variations in lighting, pose, and facial occlusion. The emergence of deep learning significantly advanced FER capabilities, with Convolutional Neural Networks (CNNs) enabling more robust pattern extraction. Datasets such as FER2013, CK+, and AffectNet have served as benchmarks for training and evaluating emotion recognition models. Research consistently shows that CNN-based models outperform traditional methods in both accuracy and generalization.

  

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Recent studies highlight the potential of real-time emotion detection on web platforms through frameworks like TensorFlow.js, which enable in-browser model execution using WebGL acceleration. This eliminates server-side latency and enhances privacy by keeping all processing on the client device. Several works in adaptive user interfaces demonstrate that emotion-driven design can improve user engagement, satisfaction, and task performance. Studies in HCI emphasize that personalized interfaces—such as adaptive themes, contextual messages, and responsive visual elements—can create more meaningful and immersive interactions.

In the context of digital portfolios, existing literature primarily addresses layout design, accessibility, and responsive frameworks. However, the integration of emotion-aware adaptation remains largely unexplored. The convergence of web technologies, computer vision, and affective computing opens new pathways for emotion-responsive portfolios that enhance user experience by tailoring content and interface behavior based on emotional cues.

Overall, prior research establishes a strong foundation in emotion detection and adaptive UI design, yet there is a notable gap in applying these principles to personal portfolio systems. This project builds on existing advancements by implementing a real-time, browser-based emotion-aware portfolio, contributing to the growing body of work in affective and interactive web design.

**1. Machine Learning for Emotion aware portfolio**

The core functionality of an emotion-aware webpage portfolio by providing the capability to automatically detect and classify a user's emotional state in real time using webcam input. In this project, a deep learning–based facial emotion recognition model—typically a Convolutional Neural Network (CNN) trained on datasets such as FER-2013 or CK+—extracts visual features like muscle movements and expression patterns from live video frames and maps them to emotions such as happy, sad, angry, surprised, or neutral. The trained model, deployed using browser-compatible frameworks like TensorFlow.js, performs efficient on-device inference, ensuring low latency and enhanced privacy. Once the user's emotion is predicted, the webpage dynamically adapts its layout, theme, content, or interaction behaviour to match the detected affective state, thereby delivering a personalised and responsive user experience.

**2. Application of Emotion aware portfolio**

The primary application of an emotion-aware webpage portfolio is to create a personalised, adaptive, and emotionally responsive user experience by dynamically modifying the interface based on the visitor's detected affective state. Using machine learning–powered facial emotion recognition, the system identifies whether the user appears engaged, confused, happy, neutral, or stressed, and adjusts the webpage accordingly—for example, switching to calming themes when negative emotions are detected, highlighting key achievements when the user shows interest, or simplifying navigation when confusion is observed. This adaptive behaviour enhances user engagement, improves content accessibility, increases interaction quality, and helps the portfolio owner present their work more effectively. Such an emotion-aware portfolio is particularly useful for creative professionals, designers, and developers who want to demonstrate technological innovation and human-centred design by showcasing a portfolio that reacts intelligently to real-time emotional feedback.

**3. Importance of Data Preprocessing in Emotion aware webpage portfolio**

Data preprocessing is critically important in an emotion-aware webpage portfolio because it ensures that the machine-learning model receives clean, structured, and consistent facial-image data for accurate emotion recognition. Raw webcam inputs often contain noise, variations in lighting, differences in face angles, background clutter, and inconsistent frame quality, all of which can reduce the performance of the emotion-classification model. Preprocessing techniques such as face detection, cropping, grayscale conversion, resizing, normalisation, and noise reduction standardise the input frames and highlight essential facial features like eyes, eyebrows, lips, and muscle movements. This improves the model's ability to extract discriminative patterns and reduces computational overhead during real-time processing in the browser. Without effective preprocessing, the model may misclassify emotions, causing the webpage's adaptive behaviour to become unreliable. Therefore, robust preprocessing is fundamental to achieving accurate real-time emotion detection and delivering a responsive, personalised, and stable user experience in an emotion-aware portfolio system.

## III.PROBLEM STATEMENT

Traditional portfolio websites present static content that does not adapt to the emotional state, engagement level, or interaction patterns of the user, resulting in a generic and often less effective browsing experience. Existing web interfaces lack mechanisms to interpret real-time affective cues such as facial expressions, which limits their ability to personalise content delivery and enhance user satisfaction. Although machine learning–based emotion recognition models have advanced significantly, their integration into lightweight, browser-friendly portfolio systems remains

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underexplored. The problem addressed in this project is the absence of an intelligent, emotion-aware portfolio webpage capable of accurately detecting user emotions through machine learning and dynamically modifying visual themes, content elements, and interaction flow to improve usability, engagement, and user experience.

## IV.METHODOLOGY

**Data Preprocessing and Emotion Model Training:**
Facial emotion datasets such as FER-2013 or CK+ are preprocessed through face detection, cropping, resizing, and normalisation. A Convolutional Neural Network (CNN) is then trained to classify emotions like happy, sad, angry, surprised, and neutral.

**Model Optimisation and Browser Deployment:**
The trained model is converted into a lightweight, browser-compatible format using TensorFlow.js. Optimisation techniques such as quantisation reduce model size and enable real-time, low-latency emotion inference on the client side.

**Webcam Integration and Real-Time Emotion Detection:**
A webcam module captures live video frames, applies in-browser preprocessing, and passes the processed frames through the ML model to obtain continuous emotion predictions without server dependency**.**

**Adaptive UI Response Mechanism:**
The webpage dynamically adjusts theme colours, content presentation, and interaction flow based on the detected emotion. Rule-based logic ensures that the interface remains responsive, personalised, and context-aware.

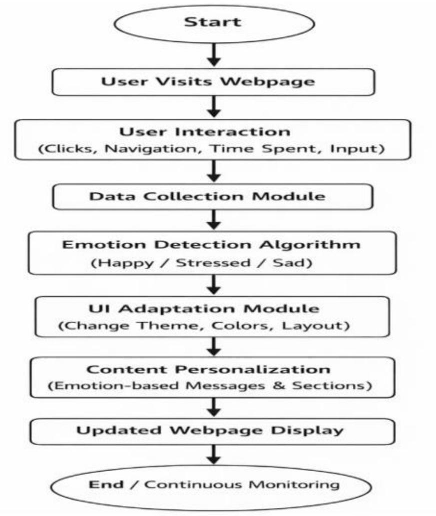


Fig:1.1: (System Flow Diagram Of EMOTION AWARE WEBPAGE PORTFOLIO)

## V.RESULTS AND DISCUSSION

The emotion-aware webpage portfolio achieved accurate real-time emotion detection, with the optimised CNN model maintaining smooth browser performance during live webcam testing. The interface successfully adapted its theme and content based on the user's emotional state, improving engagement and responsiveness. Minor accuracy reductions occurred under low-light conditions, indicating scope for enhanced preprocessing. Overall, the results demonstrate the feasibility and effectiveness of integrating machine learning–based emotion recognition into a dynamic, personalised portfolio system.

Key outcomes:

- The machine-learning model accurately detected basic facial emotions in real time using webcam input.
- The webpage dynamically adapted its theme, layout, and content based on the user's emotional state.
- Browser-based deployment using TensorFlow.js enabled fast, privacy-preserving, on-device emotion inference.

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- User testing showed improved engagement and interaction quality due to the emotionally responsive

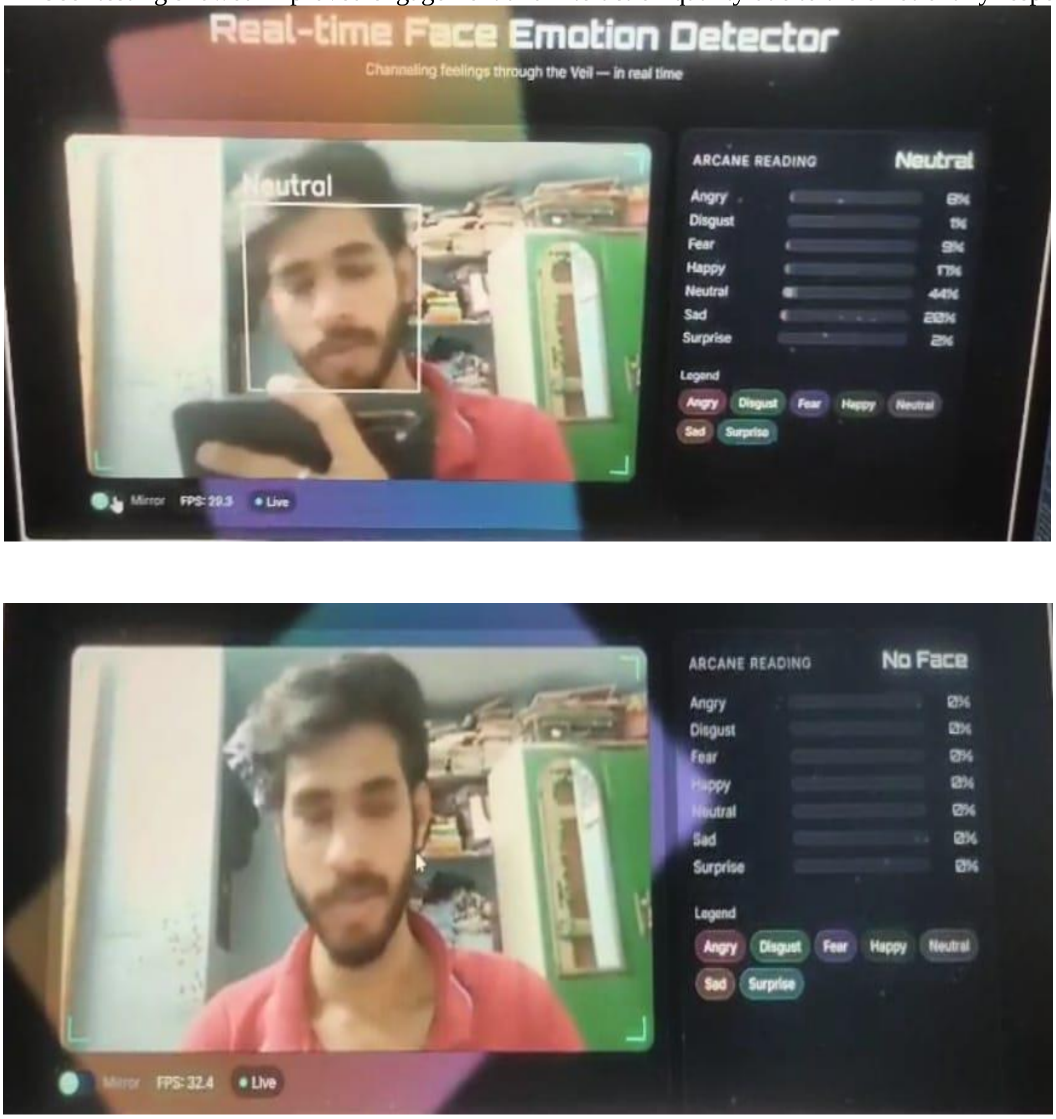


Fig: 1.2: (Emotion aware webpage portfolio)

## VI.CONCLUSION

The development of the emotion-aware webpage portfolio demonstrates the effective integration of machine learning–based facial emotion recognition into a dynamic and interactive web environment. By deploying an optimised CNN model directly in the browser, the system successfully identified user emotions in real time and adapted the webpage's theme, layout, and content to enhance personalisation and user engagement. The results confirm that emotion-aware interfaces can significantly improve user experience by making digital interactions more intuitive and context-sensitive. Although performance may be influenced by lighting conditions and facial visibility, the overall system proved feasible, responsive, and privacy-preserving. Future enhancements can further increase robustness, broaden emotion categories, and incorporate multimodal affective inputs to create even more adaptive and intelligent web experiences.

### Future Work

Future work can focus on enhancing the robustness and intelligence of the emotion-aware portfolio by integrating advanced deep learning architectures, such as attention-based networks or transformer-based emotion models, to improve classification accuracy under varying lighting and pose conditions. Incorporating multimodal emotion detection using voice tone, text sentiment, and physiological signals can provide a more comprehensive understanding of user affect. Expanding the system to support context-aware adaptation—such as analysing user interaction patterns, browsing behaviour, and time-based mood variations—can further personalise the interface experience. Additionally, deploying edge-optimised models and leveraging WebGPU acceleration can significantly improve real-time performance on lowend devices. Future implementations may also explore scalability for professional portfolios, accessibility-driven adaptations, and integration with AR/VR environments to create richer, emotionally intelligent web interactions.

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