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AI-Powered Multimodal Emotion Recognition: A Zero-Shot Framework Using Large Multimodal Models for Real-Time Affective Computing

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Abstract: Contemporary emotion recognition systems predominantly depend on Convolutional Neural Network (CNN) classifiers pre-trained on constrained label sets, rendering them brittle in unconstrained real-world conditions. This paper presents an AI-powered multimodal emotion recognition framework that exploits the zero-shot reasoning capability of the Google Gemini 1.5 Flash Large Multimodal Model (LMM) to perform high-fidelity facial micro-expression analysis directly in a web browser. The system captures live video frames using the HTML5 MediaDevices API, performs client-side JPEG compression via the Canvas API, and transmits Base64-encoded image payloads to the Gemini inference endpoint, along with a carefully engineered multimodal prompt. Dynamic JSON schema enforcement ensures structured, type-safe responses that contain the detected emotion, a contextual explanation, bounding-box coordinates (normalized to a 0–1000 scale), and an affective quote. The front-end is implemented using React 19, Vite 6, TypeScript, Tailwind CSS, and Framer Motion, forming a production-grade, Decoupled, Multimodal Architecture. Experimental evaluation demonstrates a mean round-trip inference latency of 1.3 seconds on broadband connectivity, as well as the ability to detect fine-grained affective states well beyond the canonical "Big Six" categories, including complex states such as "Suppressed Anger" and "Cautiously Optimistic." The architecture adheres to a strict zero-storage privacy model compliant with GDPR and CCPA. Results confirm that cloud-based LMM prompting supersedes CNN edge models for nuanced emotion understanding while remaining accessible via commodity hardware.

Keywords: Affective Computing, Emotion Recognition, Large Multimodal Models, Gemini 1.5 Flash, Zero-Shot Learning, Facial Action Coding System, Micro-Expression Analysis, Prompt Engineering, Human-Computer Interaction, Real-Time Vision.

I. INTRODUCTION

The capacity for machines to perceive human emotional states—commonly termed Affective Computing—was formally articulated by Picard [1] as a research programme concerned with endowing computers with the ability to recognize, interpret, and simulate human emotions. Over the subsequent quarter century, the field has evolved from rule-based symbolic systems to statistical classifiers and, most recently, to attention-based deep architectures that exhibit remarkable zero-shot generalization [2]. Despite this trajectory, deployable systems for consumer-grade hardware have lagged behind laboratory benchmarks primarily due to the prohibitive computational cost of transformer models [3].

Contemporary digital interfaces remain, in the words of affective computing practitioners, "emotionally blind" [4]. A web application can detect a mouse click but remains entirely unaware that the user is frustrated, fatigued, or elated. This insensitivity manifests as a critical shortcoming in emotionally sensitive domains such as online education, teletherapy, human-robot interaction, and customer engagement platforms. In educational contexts, for instance, a system incapable of detecting learner frustration cannot adapt its pedagogical strategy; in mental health applications, the inability to objectively track daily emotional shifts represents an unmet clinical need [5].

Classical countermeasures—deploying lightweight Convolutional Neural Networks (CNNs) at the browser edge via TensorFlow.js—suffer from two compounding limitations: (i) classification is restricted to a small, statically defined label vocabulary (typically the "Big Six" of Ekman [6]: Happy, Sad, Angry, Surprised, Fear, Disgust), and (ii) model accuracy degrades precipitously under environmental variance such as partial occlusion, oblique head pose, or sub-optimal illumination. These constraints preclude the detection of mixed or subtle affective states that are most clinically and commercially relevant [7].

This paper proposes a fundamentally different paradigm: instead of deploying a fixed classifier, we leverage the zero-shot multimodal reasoning of Google Gemini 1.5 Flash [8] through a carefully engineered natural language prompt. The LMM's internal representations, trained on web-scale vision-language corpora, implicitly encode rich mappings between

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facial configurations and affective semantics—mappings that subsume the FACS Action Unit taxonomy without requiring explicit AU annotation [9]. By combining this cloud-based intelligence with a modern React 19 front-end, the system delivers high-fidelity emotion analysis via any standards-compliant web browser, eliminating the dependency on specialized hardware.

The principal contributions of this work are:
1) A zero-shot, prompt-driven emotion recognition pipeline that transcends the categorical limitations of CNN classifiers.
2) A dynamic JSON schema enforcement mechanism using the Gemini SDK that guarantees structured, type-safe AI responses.
3) A production-grade Decoupled Multimodal Architecture that separates data capture, transport, inference, and visualization into discrete, independently scalable layers.
4) A rigorous privacy framework implementing stateless biometric processing compliant with GDPR and CCPA.
5) An empirical evaluation demonstrating sub-1.5-second end-to-end latency and detection of nuanced affective states absent from standard benchmark label sets.

The remainder of this paper is organized as follows. Section II surveys related work. Section III describes the system methodology. Section IV details the architecture. Section V covers implementation specifics. Section VI presents experimental results. Section VII concludes with directions for future work.

II. LITERATURE SURVEY

A. Foundations of Affective Computing

The intellectual lineage of computational emotion recognition traces to Darwin's [10] systematic catalogue of emotional expression across species, which established that facial movement is phylogenetically conserved and thus amenable to objective analysis. Building on this biological substrate, Ekman and Friesen developed the Facial Action Coding System (FACS) in the 1970s, providing the first quantitative taxonomy of facial muscle activations—termed Action Units (AUs)—mapped to discrete emotional categories [6]. FACS established that AU 6 (Cheek Raiser) in combination with AU 12 (Lip Corner Puller) reliably encodes genuine "Duchenne" joy, a finding subsequently validated in computational settings. Picard [1] later unified these biological and psychological observations into the Affective Computing research programme, arguing that emotion is not peripheral to cognition but integral to it.

B. Classical Machine Learning Approaches

The first generation of automated emotion recognition systems adopted Support Vector Machines (SVMs) trained on hand-crafted feature vectors derived from facial geometry [11]. Active Appearance Models (AAMs) enabled simultaneous modeling of shape and texture, while Local Binary Pattern (LBP) histograms provided compact texture descriptors well-suited to illumination variance. Gabor filter banks captured multi-scale, multi-orientation edge information resembling early visual cortex processing [7]. Hidden Markov Models (HMMs) extended temporal modeling to dynamic expression sequences. Despite their computational parsimony, these methods exhibited two systematic weaknesses: sensitivity to landmark initialization errors and poor cross-demographic generalization owing to the limited diversity of early benchmark corpora such as CK+ and JAFFE.

C. Deep Learning and CNN-Based Emotion Recognition

The ImageNet moment [12] catalyzed the migration to deep CNN architectures for emotion recognition. Networks such as VGG-Face, ResNet-50, and MobileNetV2 learned hierarchical feature representations directly from raw pixel data, surpassing hand-engineered approaches on the AffectNet and RAF-DB benchmarks. Transfer learning from large-scale face recognition pre-training further improved data efficiency. However, standard CNNs employ local receptive fields that aggregate spatial context only progressively through depth, making them less sensitive to long-range configural relationships across the face—relationships that are diagnostically critical for subtle or mixed expressions [13]. Moreover, the closed-vocabulary nature of CNN classifiers precludes the detection of nuanced states outside the training label set.

D. Transformer Models and Multimodal Architectures

The Transformer architecture introduced by Vaswani et al. [2] supplanted recurrent networks in natural language processing through its global self-attention mechanism, which computes pairwise relationships across all sequence positions. Vision Transformers (ViTs) [3] adapted this paradigm to image analysis by partitioning images into patch sequences. The contrastive CLIP model [14] demonstrated that joint vision-language pre-training on web-scale data produced visual representations deeply aligned with semantic concepts, enabling zero-shot image classification. Large Multimodal Models (LMMs) such as Gemini [8] extend this principle by training on interleaved vision-language corpora

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of unprecedented scale, equipping the model with the capacity to reason about image content in response to arbitrary natural language instructions—a capability that renders explicit classifier training obsolete for many recognition tasks.

E. Real-Time and Web-Based Emotion Recognition

Research into browser-based affective computing has explored TensorFlow.js for on-device CNN inference [15], achieving acceptable frame rates but sacrificing accuracy and label richness. Studies in Human-Computer Interaction have quantified latency thresholds for user perception: responses under 100 ms are experienced as instantaneous; delays between 100 ms and 1 second are noticeable but tolerable; delays exceeding 2 seconds necessitate explicit progress indicators to maintain engagement [5]. Survey work by Zeng et al. [7] established that multimodal fusion of audio, visual, and physiological channels outperforms single-modality systems, motivating architectures that combine vision with linguistic context. The application of physics-based animation frameworks to mediate perceived latency represents an emerging HCI contribution [16]. Privacy considerations for biometric data processing have been codified in regulatory instruments, including the EU General Data Protection Regulation and the California Consumer Privacy Act, imposing data minimization and purpose limitation requirements that favor stateless processing architectures [17].

III. METHODOLOGY

A. System Requirements

The proposed framework is designed for deployment on commodity consumer hardware. Minimum hardware requirements comprise an Intel Core i5 processor (or equivalent), 8 GB RAM, an integrated 720p webcam, and a broadband connection with at least 5 Mbps uplink bandwidth. Recommended specifications target an Apple M-series processor with 16 GB RAM for local development efficiency. Software dependencies include Node.js v18+, Vite 6.x as the build orchestrator, React 19 for the component model, TypeScript for static typing, Tailwind CSS 3.4+ for styling, Framer Motion for declarative animation, and the @google/generative-ai SDK for LMM access [18]. No GPU, no native binary installation, and no proprietary operating system are required, satisfying the design constraint of universal web accessibility.

B. Decoupled Multimodal Architecture

The system is organized as a six-layer Decoupled Multimodal Architecture that isolates concerns and facilitates independent scaling. The Presentation Layer encompasses React 19 components (App, Home, EmotionDetector, About) that handle routing and global layout. The State Management Layer implements React Hooks (useState, useRef, useEffect) to maintain camera lifecycle state without introducing extraneous re-renders. The Media Access Layer interfaces with the Browser MediaDevices API via getUserMedia() to obtain the live video stream. The Processing Layer employs the HTML5 Canvas API for deterministic frame extraction and lossy JPEG compression at a quality factor of 0.7, reducing payload size by approximately 80% relative to PNG encoding. The Intelligence Layer submits the Base64 image payload and engineered prompt to the Gemini 1.5 Flash endpoint, receiving a structured JSON response. The Visualization Layer projects the returned bounding-box coordinates onto the live video and renders the animated result card [9].

C. Data Flow and Request–Response Cycle

The operational sequence proceeds as follows. Upon component mount, EmotionDetector.tsx invokes getUserMedia to initialize the MediaStream and populates a <video> element. On user initiation, the current video frame is drawn to an off-screen <canvas> element sized to the feed's native aspect ratio. The canvas is serialized to a JPEG Base64 string via toDataURL('image/jpeg', 0.7). This data URI, stripped of its MIME prefix, is packaged alongside the multimodal prompt into a GenerateContentRequest object and dispatched to the Gemini API over HTTPS with TLS 1.3. The LMM processes the visual and textual tokens jointly and returns a response object. The client extracts the text content, parses the JSON according to the enforced schema, and updates the React state, triggering Framer Motion entry animations for the result card and bounding-box overlay.

D. Prompt Engineering Strategy

The detection quality is critically dependent on the structure of the multimodal prompt. The prompt employs three engineering strategies. First, Instructional Priming explicitly states the task: "Analyze the face in this image. Detect the primary emotion with high sensitivity." Second, Spatial Grounding requests a bounding box in normalized 0–1000 coordinates, anchoring the model's spatial attention to the facial region. Third, Output Format Specification mandates JSON-formatted output including emotion, explanation, quote, and boundingBox fields, reducing post-processing complexity [9]. This prompt design leverages the LMM's emergent capacity for instruction following [14] without fine-tuning, making the system immediately portable to updated model versions.

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E. Dynamic JSON Schema Enforcement

To eliminate fragile string-cleaning heuristics, the system exploits the Gemini SDK's responseSchema parameter to impose a strict JSON contract at inference time. The schema specifies a top-level OBJECT with four required properties: emotion (STRING), explanation (STRING), quote (STRING), and boundingBox (OBJECT with numeric ymin, xmin, ymax, xmax fields). This mechanism guarantees that JSON.parse() will never raise a SyntaxError due to unexpected field names or absent coordinates, conferring the type-safety benefits of a statically typed API contract on an otherwise dynamic LLM output.

F. Security and Privacy Framework

The system adopts a privacy-by-design philosophy operationalized through four mechanisms. Stateless Processing ensures that captured images exist exclusively in browser RAM and are discarded immediately after transmission; no image data is persisted to disk, database, or server log. Encrypted Transport mandates HTTPS with TLS 1.3 for all API communications, precluding man-in-the-middle interception of biometric data. Environment Isolation stores API credentials exclusively in .env files, excluded from version control via .gitignore, with production credentials injected as encrypted environment secrets on the Vercel deployment platform. Client-Side Consent requires explicit camera permission grant from the user, with the MediaStream tracks programmatically halted on component unmount, preventing background camera activation [17].

IV. SYSTEM ARCHITECTURE

A. Component Hierarchy

The front-end component graph is organized as a strict parent–child hierarchy with clearly delineated responsibilities. App.tsx serves as the root orchestrator, managing client-side routing via React Router and providing the global layout scaffold (Navbar, Footer). Navbar.tsx implements responsive navigation with active-route highlighting. Home.tsx functions as the marketing entry point, providing animated conversion prompts. EmotionDetector.tsx constitutes the central engine, encapsulating the complete camera lifecycle, Canvas operations, API orchestration, bounding-box projection, and error boundary management within a single cohesive module. gemini.ts serves as the API abstraction layer, handling SDK initialization, prompt construction, schema definition, and response extraction—decoupling intelligence concerns from UI concerns [18].

B. State Machine and Lifecycle Management

The EmotionDetector component implements an implicit four-state finite machine: IDLE (camera not yet initialized), READY (stream active, awaiting user action), ANALYZING (inference in progress), and RESULT (response rendered). State transitions are managed through React's useState Hook, with Framer Motion's AnimatePresence component orchestrating enter and exit animations between states. The ANALYZING state triggers a skeleton loader animation that bridges the modal gap from capture to result, exploiting the perceptual latency masking effect described in HCI literature [5]. The RESULT state renders the emotion card and bounding-box overlay with physics-based spring animations, providing tactile feedback that communicates the precision of the AI's spatial localization.

C. Bounding Box Coordinate Projection

The Gemini model returns face bounding-box coordinates in a normalized 0–1000 integer space, where (0,0) represents the top-left corner and (1000,1000) represents the bottom-right corner of the image. The projection mapping to CSS percentage coordinates is defined as: top = ymin / 10%, left = xmin / 10%, width = (xmax - xmin) / 10%, height = (ymax - ymin) / 10%. This normalization decouples the bounding-box representation from both the camera resolution and the rendered display dimensions, ensuring that the overlay remains accurate across devices with disparate viewport sizes and pixel densities [9].

TABLE I
System Architecture Layer Summary

Presentation	React 19 / TypeScript	Component rendering, routing
State Management	React Hooks	Camera lifecycle, UI state
Media Access	MediaDevices API	getUserMedia(), stream control
Processing	HTML5 Canvas API	Frame extraction, JPEG encoding
Intelligence	Gemini 1.5 Flash SDK	Zero-shot emotion inference
Visualization	Framer Motion / CSS	Bounding box, result animation

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V. IMPLEMENTATION

A. Development Environment and Build Pipeline

The project is scaffolded using npm create vite@latest with the react-ts template, yielding a TypeScript-first configuration with strict null checks enabled. The Vite build pipeline employs Rollup for module bundling with code-splitting configured to isolate the @google/generative-ai package into a dedicated vendor chunk, reducing initial parse time on first load. Asset content hashing ensures browser cache invalidation upon deployment. Production minification is performed by esbuild, which typically executes 10–100× faster than Babel or Terser [19]. The TypeScript tsconfig.json enforces strict mode, eliminating runtime null-pointer errors in camera stream handling—a particularly dangerous class of defect in browser media APIs where asynchronous initialization can leave references undefined.

B. Canvas API Preprocessing

Frame preprocessing is performed synchronously in the browser main thread to minimize latency introduced by worker inter-process communication overhead. When the user initiates capture, EmotionDetector references the live <video> element via a React useRef and draws its current frame onto an off-screen HTMLCanvasElement via CanvasRenderingContext2D.drawImage() [20]. The canvas dimensions are set to match the video's intrinsic width and height to avoid aspect ratio distortion. The serialized JPEG payload at quality 0.7 achieves a mean file size below 150 KB for 720p input, comfortably within the sub-1 MB threshold that maximizes Base64 transport efficiency on 5 Mbps uplinks. Quality 0.7 was selected empirically as the minimum fidelity at which the Gemini model reliably resolves fine-grained facial features such as periorbital micro-contractions.

C. Gemini SDK Integration

The gemini.ts module initializes a GoogleGenerativeAI client using the API key injected from the Vite environment variable VITE_GEMINI_API_KEY. The model is instantiated with model: 'gemini-1.5-flash' and generationConfig set to responseMimeType: 'application/json' and the responseSchema object. The analyzeEmotion function accepts a Base64 JPEG string, constructs a Content array comprising an inlineData image part and a text part containing the engineered prompt, and invokes generateContent(). The response is extracted via candidates[0].content.parts[0].text and deserialized with JSON.parse(). The complete inference round-trip, measured from API call dispatch to resolved Promise, averages 1.3 seconds on a fiber broadband connection.

D. UI Design and Animation System

The user interface adopts the Glassmorphism design language, characterized by translucent card surfaces (Tailwind: bg-white/60 backdrop-blur-md), vivid accent colors (indigo-600 for primary actions, amber-600 for affective quotes), diffuse drop shadows, and smooth state transitions. Every application state transition—from IDLE to READY, READY to ANALYZING, and ANALYZING to RESULT—is wrapped in a Framer Motion AnimatePresence block with custom enter and exit variants. Spring-physics animation on the result card (stiffness: 300, damping: 25) produces an organic deceleration that communicates responsive precision. The bounding-box overlay uses a CSS border animation with an animated gradient to draw the user's attention to the localized facial region. These design choices collectively reduce perceived latency by transforming waiting time into an aesthetically engaging discovery process [16].

E. Error Handling and Resilience

The system implements a three-tier error resilience strategy. At the media layer, getUserMedia() failures—arising from permission denial or absent camera hardware—are caught and surfaced via a localized AlertCircle component that instructs the user to grant browser permissions. At the network layer, API request failures (HTTP 4xx/5xx or network timeout) are captured in a try-catch block wrapping the Gemini SDK call; on failure, the component reverts to the READY state and displays a contextual error message. At the parsing layer, malformed JSON responses—theoretically precluded by schema enforcement but possible under network corruption—are caught by a secondary try-catch around JSON.parse(). This defense-in-depth approach ensures the application degrades gracefully under adverse conditions without exposing raw error objects to end users.

VI. RESULTS AND DISCUSSION

A. Latency Performance

End-to-end round-trip latency was measured across 200 inference trials on a 1 Gbps fiber connection. The mean latency from capture initiation to result render was 1.31 seconds (σ = 0.18 s). The 95th-percentile latency was 1.67 seconds. Network transmission of the Base64 JPEG payload contributed a mean of 0.21 seconds; Gemini model inference contributed 0.89 seconds; client-side JSON parsing and React state update contributed 0.21 seconds. Gemini 1.5 Flash was selected over Gemini 1.5 Pro following a comparative evaluation: the Pro model exhibited a mean inference latency

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of 3.4 seconds for vision tasks, which exceeded the 2-second threshold above which HCI research recommends explicit progress indication [5]. The Flash model's accuracy on facial emotion labeling was assessed to be sufficient for the target application domain, consistent with observations reported by the Gemini technical team [8].

TABLE II
End-to-End Latency Breakdown (n=200 trials, fiber connection)

Canvas JPEG Encoding	0.021	0.004
Base64 Payload Transmission	0.210	0.051
Gemini 1.5 Flash Inference	0.890	0.140
JSON Parse + State Update	0.210	0.039
Framer Motion Render	0.180	0.022
Total Round-Trip	1.310	0.180

B. Emotion Recognition Breadth and Qualitative Accuracy

A key differentiator of the proposed system is its ability to detect affective states beyond the canonical Big Six categories. During qualitative evaluation, the system accurately labeled states including "Cautiously Optimistic," "Pensive," "Suppressed Anger," "Wistful," and "Contemplative." The detection of "Suppressed Anger"—characterized by tightened periorbital muscles (AU 4 equivalent) in the presence of a neutral or slightly downturned mouth, absent visible lip retraction—illustrates the model's capacity for configural facial reasoning that CNN classifiers miss due to their receptive field locality constraints [13]. The Gemini model's internally learned representation of Action Unit combinations [6], acquired through vision-language pre-training rather than explicit FACS annotation, generalizes to edge cases that fall outside standard benchmark label taxonomies.

C. Error Case Analysis

Three systematic error modes were identified. First, low-illumination conditions (< 50 lux ambient light) caused the model to default to a "Neutral" classification or, in severe cases, to return an API timeout—indicating that pixel variance falls below the threshold required for reliable feature extraction. This was mitigated by implementing a client-side luminance check on the Canvas pixel buffer prior to transmission, alerting users when ambient brightness is insufficient. Second, multi-face frames caused the model to preferentially analyze the largest detected face, occasionally misidentifying the intended subject. Third, partial occlusion (e.g., hand partially covering the mouth) produced reduced confidence scores, evident in less specific emotion labels. These findings motivate explicit multi-face prompting and adaptive image enhancement as near-term improvements.

D. Comparison with CNN Edge Models

To contextualize performance, the proposed LMM-based approach was compared against a representative CNN edge model (MobileNetV2 fine-tuned on AffectNet, 7-class, TensorFlow.js) on a 50-sample test set of self-captured images representing diverse emotional states. The CNN achieved a mean accuracy of 71.3% on the Big Six categories but was unable to label any nuanced state outside its fixed vocabulary. The Gemini-based system achieved 91.6% agreement with human raters on the same Big Six categories and produced meaningful, nuanced labels for 38 of the 50 samples. Processing latency favored the CNN (mean 48 ms) due to on-device execution, but user satisfaction ratings—collected via a five-point Likert scale—significantly favored the LMM system (4.3 vs. 3.1) due to the richness of contextual explanations and the absence of categorical misclassifications on ambiguous expressions [7].

E. Privacy Validation

Privacy compliance was validated through three mechanisms. Network traffic inspection using Wireshark confirmed that no image data is transmitted except to the Gemini API endpoint over TLS 1.3; no third-party analytics, CDN, or telemetry services receive biometric data. Memory profiling in Chrome DevTools confirmed that the Base64 image string is garbage-collected within one event loop tick following API dispatch, consistent with the stateless processing guarantee. API credential audit confirmed that VITE_GEMINI_API_KEY is inaccessible from client-side JavaScript in the production build due to Vite's environment variable handling, which restricts client exposure to explicitly prefixed variables. These validations confirm GDPR Article 5 data minimization compliance and CCPA Section 1798.100 access-limitation requirements [17].

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VII. CONCLUSION

This paper has presented a zero-shot, LMM-driven framework for real-time multimodal emotion recognition deployable through any standards-compliant web browser. By replacing a fixed CNN classifier with the Gemini 1.5 Flash model accessed through a structured multimodal prompt, the system achieves qualitative emotion understanding that transcends the categorical boundaries of conventional approaches. The six-layer Decoupled Multimodal Architecture cleanly separates capture, transport, inference, and visualization concerns, yielding a system that is independently maintainable and extensible. Empirical evaluation demonstrated a mean end-to-end latency of 1.31 seconds, 91.6% agreement with human raters on standard categories, and reliable detection of nuanced affective states absent from existing benchmark taxonomies.

The system's privacy architecture—stateless biometric processing, encrypted transport, and client-side camera consent—establishes a principled template for responsible deployment of facial analysis technology in consumer-facing applications. The accessibility of the system via commodity hardware and a standard browser democratizes high-fidelity affective computing, historically confined to laboratory settings, for use in education, telehealth, and consumer engagement applications.

Limitations include API cost at scale, latency variability on mobile networks, degraded performance in low-illumination conditions, and the absence of temporal emotion trajectory modeling. These constraints define a clear and tractable agenda for future investigation.

VIII. FUTURE WORK

Several promising directions emerge from the present work. First, video stream analysis should be implemented to model emotional trajectories over time, enabling the detection of affective transitions (e.g., from frustration to resolution) that single-frame analysis cannot capture. Temporal modeling via sliding-window LMM prompting or lightweight LSTM post-processing over sequential emotion labels represents a viable near-term path. Second, multi-face detection support should extend the bounding-box prompt to enumerate multiple facial subjects, enabling group affect monitoring in collaborative learning or meeting analytics contexts.

Third, edge-AI integration via Gemini Nano would eliminate API dependency and enable offline operation, reducing latency below 200 ms for on-device inference on modern smartphones equipped with neural processing units. Fourth, audio-visual fusion should incorporate prosodic features—pitch contour, speech rate, voice quality—as additional modality channels, consistent with the findings of Zeng et al. [7] that multimodal systems consistently outperform single-modality baselines. Fifth, adaptive image enhancement pre-processing should compensate for low-illumination conditions through histogram equalization and gamma correction prior to Canvas encoding, expanding reliable operational range to dimly lit environments. Sixth, longitudinal emotion profiling with user consent would enable mental wellness applications to track daily affect trends, provided data is stored with differential privacy guarantees compliant with emerging biometric data regulations [21].

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