Affectoo: AI powered Mental health game

An AI-Powered Emotion-Adaptive Mental Wellness Game

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***Abstract*—In the domain of AI and Mobile Application Development, emotional self-regulation remains a significant challenge in contemporary digital lifestyles. Affectoo (AI Powered Mental Health Game) is a cross-platform mobile application designed to assist users in identifying, tracking, and managing their emotional states through a multimodal, AI-driven framework. The system integrates on-device machine learning for facial expression recognition using a fine-tuned FER+ model deployed via TensorFlow Lite, combined with natural language processing techniques for sentiment and emotion analyses of user journal entries. By performing multimodal fusion of visual and textual inputs, the application estimates the user's primary emotional state with improved contextual accuracy. Based on the detected emotion, Affectoo dynamically recommends adaptive micro-interventions in the form of interactive 3D modules and gamified activities. These include guided breathing exercises, rhythm-based cognitive tasks, and emotion-responsive interaction mechanics designed to promote emotional awareness and gradual mood stabilization in users. A 3D avatar system visually represents emotional progression and enhances user engagement through gamification principles. The application was developed using the Flutter framework and employed a local SQLite database to ensure secure offline-first mood tracking. By integrating edge AI, multimodal emotion recognition, and adaptive game-based interaction within a mobile ecosystem, this project demonstrates a scalable and privacy-conscious approach to support everyday emotional self-regulation without functioning as a clinical diagnostic tool.**

***Index Terms*—Affective Computing, Edge AI, Multimodal Emotion Recognition, Flutter, TensorFlow Lite, Gamification, Mental Wellness Systems.**

I. Introduction

Mental health has become a significant concern in modern society due to increasing academic pressure, professional demands, social expectations, and rapid lifestyle changes. Emotional well-being plays a crucial role in an individual's productivity, interpersonal relationships, and overall quality of life. However, many individuals experience frequent stress, anxiety, and mood fluctuations without having access to immediate and personalized support systems.

In recent years, mobile-based mental wellness applications have emerged as accessible tools for emotion tracking and self-regulation. Most existing solutions rely on manual input methods such as journaling or provide static self-help content, which often lack personalization and real-time responsiveness. These limitations reduce user engagement and fail to deliver timely interventions when they are most needed.

To address these challenges, this paper presents Affectoo, a multimodal emotion-adaptive mobile system designed to assist users in identifying, tracking, and regulating their emotional states. The system integrates facial expression recognition and text-based sentiment analysis to estimate the user’s emotional condition with improved contextual accuracy. Unlike traditional systems, Affectoo performs on-device processing using TensorFlow Lite, ensuring user privacy, reduced latency, and offline functionality.

Affectoo follows a “Check-in and Play” approach, where users can quickly express their emotional state through facial input or journaling and immediately receive adaptive interventions. These interventions are delivered through interactive 3D modules and gamified activities, including guided breathing exercises and rhythm-based cognitive tasks. A dynamic 3D avatar visually represents emotional states, enhancing user engagement and providing intuitive feedback.

By combining multimodal emotion recognition, edge AI, and gamified interaction within a unified mobile platform, Affectoo transforms conventional mood tracking into an interactive and responsive emotional support system. This work contributes toward the development of scalable, privacy-preserving, and user-centric mental wellness technologies that support everyday emotional self-regulation.

II. Literature Survey

Recent advancements in mental health technologies have led to the development of intelligent systems capable of analyzing and interpreting human emotions. Affective computing has emerged as a key research area, focusing on enabling machines to recognize, process, and respond to human emotional states. One of the widely studied approaches in this domain is facial expression recognition using deep learning techniques, particularly Convolutional Neural Networks (CNNs), which have demonstrated high accuracy in identifying basic human emotions from visual data [1].

In parallel, Natural Language Processing (NLP) has been extensively used for sentiment analysis and emotion detection from textual data. Techniques such as lexicon-based methods and deep learning models, including Long Short-Term Memory (LSTM) networks, are capable of capturing contextual and semantic meaning in user-generated text [2]. However, systems relying solely on textual analysis often fail to capture implicit emotional cues such as tone, sarcasm, or facial expressions.

To overcome the limitations of unimodal systems, multimodal emotion recognition has gained significant attention. Multimodal approaches combine information from multiple sources such as facial expressions, speech, and text to improve the accuracy and robustness of emotion detection. Studies have shown that integrating multiple modalities leads to more reliable and context-aware predictions compared to single-modality systems [3–5].

In addition to emotion detection, user engagement plays a critical role in the effectiveness of mental wellness applications. Gamification has been widely adopted to enhance user interaction by incorporating elements such as rewards, feedback, and immersive environments. Research indicates that gamified systems can significantly improve user motivation, adherence, and emotional engagement [10,11].

Despite these advancements, many existing mental health applications implement these technologies in isolation. Most systems either focus on emotion detection without providing actionable interventions or offer static self-help content without real-time personalization. Furthermore, reliance on cloud-based processing raises concerns related to data privacy and latency.

The proposed system, Affectoo, addresses these gaps by integrating multimodal emotion recognition with on-device processing and adaptive gamified interventions within a unified mobile platform. By combining facial and textual analysis with real-time feedback mechanisms, the system aims to provide a more responsive, engaging, and privacy-preserving approach to emotional self-regulation.

III. SYSTEM ANALYSIS

A. User Requirements and Feasibility

The proposed system, Affectoo, is designed to assist individuals experiencing emotional fluctuations by providing a simple, intuitive, and responsive platform for emotional self-regulation. The primary requirement is to minimize user effort while accurately capturing emotional states. The system supports both passive and active inputs, allowing users to express emotions through facial expressions or text-based journaling.

From a technical perspective, the feasibility of the system is supported by advancements in mobile hardware, particularly the availability of Neural Processing Units (NPUs) capable of executing deep learning models efficiently. The use of TensorFlow Lite enables real-time inference on mobile devices with minimal latency. Additionally, the system operates entirely on-device, ensuring data privacy and eliminating dependency on cloud infrastructure.

Economically, the system is cost-effective as it leverages open-source frameworks and does not require server-side processing. The offline-first design reduces operational costs and enhances accessibility in low-connectivity environments.

B. Input Modalities and Knowledge Base

Affectoo employs a multimodal approach to emotion recognition by integrating multiple input channels:

- Visual Input: The front-facing camera captures facial expressions, which are processed using a Convolutional Neural Network to detect emotional features.
- Textual Input: User journal entries are analyzed using Natural Language Processing techniques to determine sentiment polarity and emotional intensity.
- Explicit Feedback: Users can manually adjust their emotional state using a slider interface, providing ground truth data for calibration.
- Historical Context: Previous emotional logs are stored locally to identify behavioral patterns and improve future predictions.

This combination of inputs enables a more comprehensive understanding of the user’s emotional state compared to single-modality systems.

C. Proposed Multimodal Ecosystem

The system consists of two independent AI processing modules: a facial emotion recognition model and a text-based sentiment analysis model. Each module generates an emotion prediction along with a confidence score. The fusion mechanism corresponds to the architecture shown in Fig. 1.

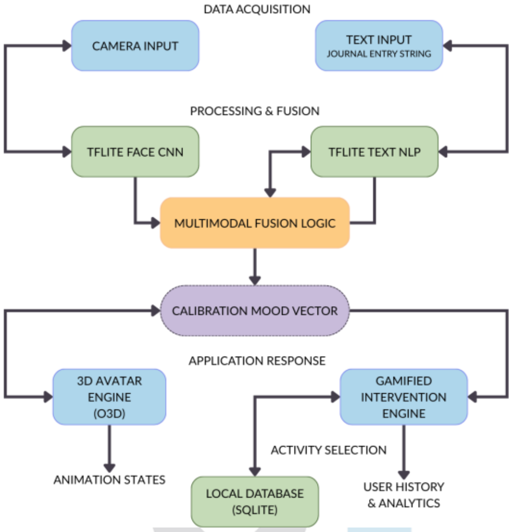

Fig. 1. Multimodal Emotion Recognition and Adaptive Response Architecture of Affectoo

A fusion mechanism combines these outputs using weighted decision logic. In cases of conflicting predictions, the system prioritizes textual input due to its higher contextual reliability. The final output is represented as a unified emotional state vector, which drives subsequent system behavior.

D. Limitations of Existing Systems

Traditional mental wellness applications primarily rely on manual journaling or static content delivery. These approaches introduce several limitations, including high cognitive effort, lack of real-time feedback, and reduced user engagement.

Additionally, unimodal emotion recognition systems often produce inaccurate results due to the absence of contextual information. Cloud-based solutions further introduce concerns related to latency, privacy, and data security.

E. Core Functional Modules

The Affectoo system is structured into the following key modules:

1. Perception Module: Responsible for capturing visual and textual inputs from the user.
2. Inference Module: Processes input data using machine learning models to detect emotional states.
3. Calibration Module: Applies multimodal fusion techniques to resolve conflicts and improve accuracy.
4. Response Module: Controls the behavior of the 3D avatar based on the detected emotion.
5. Intervention Module: Delivers adaptive gamified activities designed to regulate emotional states.

F. Software and Hardware Requirements

The system is developed using the Flutter framework for cross-platform compatibility and employs TensorFlow Lite for on-device machine learning inference. Data is stored securely using SQFLite, ensuring local persistence and privacy.

The application requires a mobile device with a front-facing camera, a minimum of 4GB RAM, and support for Android 8.0 or iOS 12.0 and above. These specifications ensure smooth execution of real-time processing and interactive graphical components.

IV. DESIGN ARCHITECTURE

A. High-Level Architecture

The Affectoo system follows a modular, local-first architecture designed for real-time emotion recognition and adaptive response generation. The system is divided into three primary layers: data acquisition, processing and fusion, and application response.

The data acquisition layer captures user inputs through the front-facing camera and text-based journal entries. These inputs are processed independently by dedicated machine learning models, including a Convolutional Neural Network for facial emotion recognition and a Natural Language Processing model for text sentiment analysis. The outputs from these models are combined using a multimodal fusion mechanism to generate a unified emotional state.

The high-level system architecture is illustrated in Fig. 2.

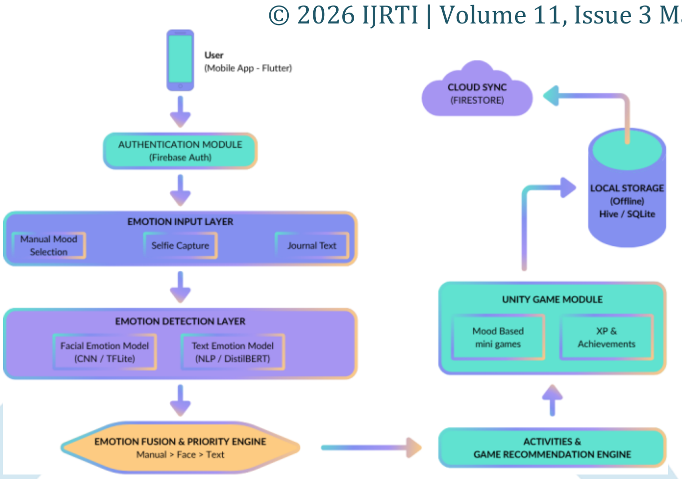

Fig. 2. High-Level System Architecture of Affectoo

B. User Emotional Workflow

The system follows a structured “Check-in and Play” workflow to minimize user effort and provide immediate feedback. The process begins with emotion sensing through visual or textual input, followed by validation and preprocessing. The inference stage applies machine learning models to detect emotional states, which are then calibrated using fusion logic.

Based on the calibrated emotional state, the system transitions into the response phase, where adaptive interventions are delivered through gamified modules and a responsive 3D avatar.

The workflow of user interaction is illustrated in Fig. 3.

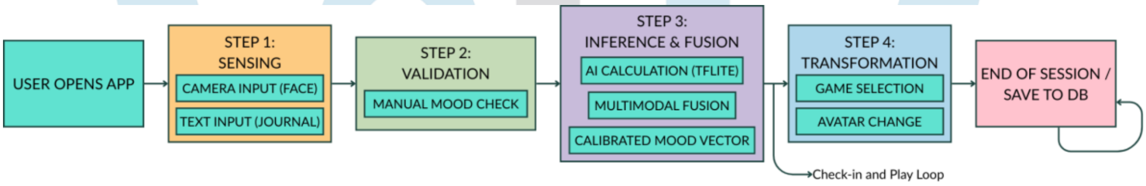

Fig. 3. User Emotional Interaction Workflow

C. UML Diagrams

To provide a structured representation of system design, multiple UML diagrams are used to describe different aspects of the Affectoo system.

• Use Case Diagram: Illustrates interactions between the user and the system, including emotion detection, journaling, and engagement with interventions.

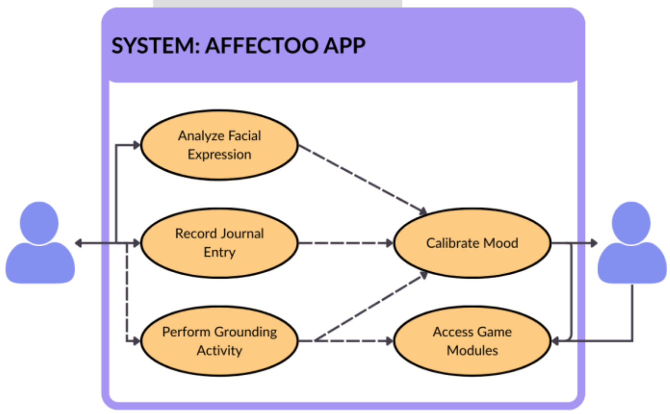

Fig. 4. Use Case Diagram of Affectoo System

• Class Diagram: Represents the internal structure of the system, including key components such as MoodController, AIInterpreter, AvatarManager, and GameEngine.

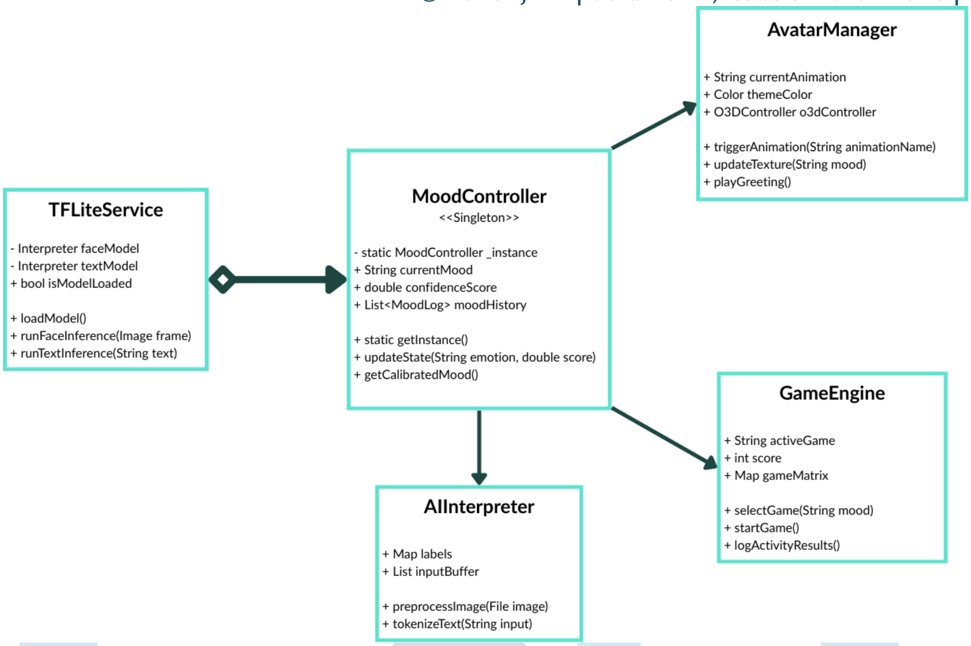

Fig. 5. Class Diagram of System Components

• Sequence Diagram: Demonstrates the flow of communication between system components during real-time emotion detection and response generation.

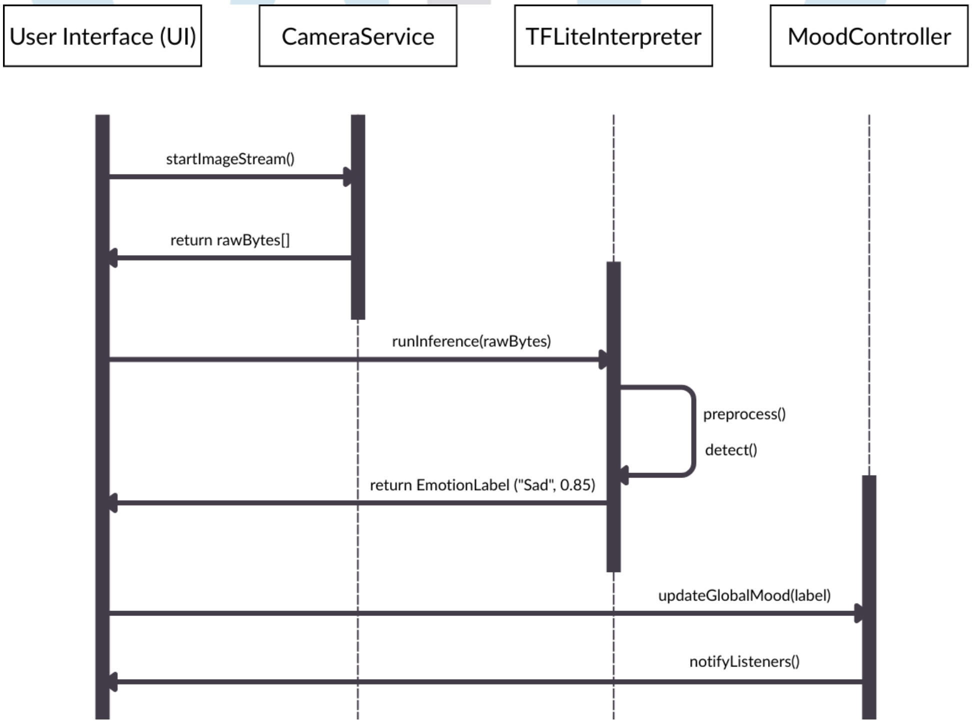

Fig. 6. Sequence Diagram for Emotion Processing Pipeline

• Activity Diagram: Describes the step-by-step flow of operations involved in emotion sensing, inference, and intervention.

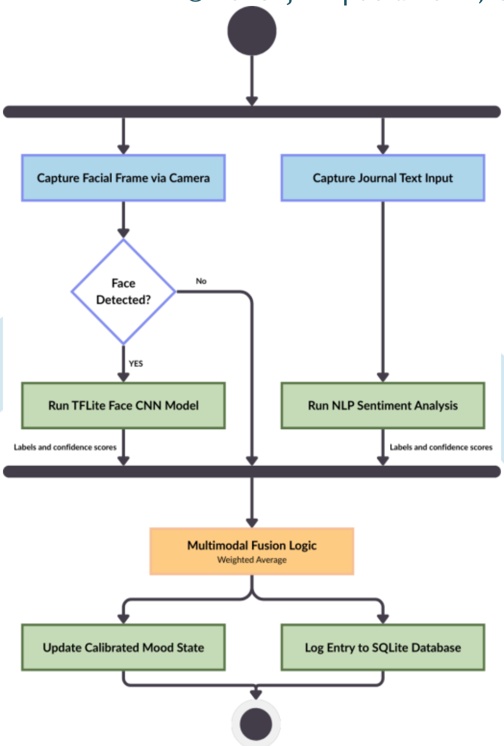

Fig. 7. Activity Diagram of System Workflow

D. Data Flow and Storage

The system maintains a continuous data flow between input, processing, and response modules. All user data, including emotional states, journal entries, and interaction logs, are stored locally using an SQLite database. This local storage mechanism ensures data privacy while enabling historical analysis and pattern recognition. The stored data is used to improve system responsiveness and personalize future interventions.

V. MODULAR DESCRIPTION

A. Software Architecture

The Affectoo system follows a modular software architecture based on the Model-View-Controller (MVC) design pattern. This approach ensures a clear separation between the user interface, data processing, and application logic. The MoodController acts as the central coordinator, managing communication between the input modules, machine learning models, and output systems.

The system utilizes asynchronous processing to maintain smooth user interaction. Background execution of machine learning tasks ensures that real-time emotion detection does not affect the responsiveness of the user interface.

B. Cross-Platform Development Tools

The application is developed using the Flutter framework, which enables cross-platform deployment on both Android and iOS devices. Flutter's rendering engine provides high-performance graphics, allowing seamless integration of interactive 3D elements.

TensorFlow Lite is used for deploying machine learning models on mobile devices. It provides optimized inference capabilities with support for hardware acceleration, ensuring efficient execution of deep learning models.

C. Flutter SDK and Dart Language

Flutter uses a widget-based architecture that allows rapid development of responsive user interfaces. The Dart programming language supports both Just-In-Time (JIT) and Ahead-Of-Time (AOT) compilation, enabling fast development cycles and optimized runtime performance.

Dart isolates are used to offload computationally intensive tasks such as emotion inference, ensuring that the main UI thread remains responsive during execution.

D. TFLite Interpreter Integration

The machine learning models are integrated using the TensorFlow Lite interpreter. The facial emotion recognition model processes preprocessed grayscale images, while the text analysis model processes tokenized input sequences.

Inference is executed using hardware acceleration when available, such as GPU or Neural Processing Units. The data pipeline includes preprocessing, model inference, and postprocessing steps to convert raw outputs into meaningful emotional states.

E. 3D Asset Pipeline

The system incorporates a 3D avatar designed using low-polygon modeling techniques to ensure optimal performance on mobile devices. The avatar is stored in GLB format and uses Physically Based Rendering (PBR) materials for visual realism.

Skeletal rigging and animation techniques are applied to enable smooth transitions between different emotional states. The lightweight design ensures minimal impact on system resources while maintaining visual quality.

F. Rendering and Animation System

The 3D avatar is rendered using a real-time rendering engine integrated within the Flutter environment. The animation system is based on a state machine that controls transitions between different emotional expressions.

Procedural animation techniques are used to simulate natural behaviors such as breathing and eye movement. These subtle animations enhance user engagement and provide intuitive visual feedback.

G. Input Data Preprocessing

Visual input is preprocessed by resizing images to a fixed resolution and converting them to grayscale to reduce computational complexity. Additional techniques such as normalization and histogram equalization are applied to improve model performance.

Textual input is processed using tokenization, stop-word removal, and vectorization techniques. The processed text is converted into numerical representations suitable for input into machine learning models.

H. Data Persistence and Analytics

All user data is stored locally using an SQLite database to ensure privacy and offline accessibility. The stored data includes emotional logs, journal entries, and user interaction history.

An analytics component processes this data to identify patterns and trends in user behavior. These insights are used to personalize future interventions and improve system effectiveness.

I. Mood Calibration Mechanism

The system employs a weighted fusion mechanism to combine outputs from facial and textual analysis models. Each modality is assigned a confidence score, and the final emotional state is determined using a weighted decision function.

Temporal smoothing techniques are applied to prevent abrupt changes in detected emotions. The calibrated emotional state is mapped onto a valence-arousal model, enabling the system to select appropriate interventions based on the user's emotional quadrant.

VI. ALGORITHM AND DEPLOYMENT

A. Convolutional Neural Network for Facial Emotion Recognition

The facial emotion recognition module is based on a Convolutional Neural Network (CNN) architecture optimized for mobile deployment. The model processes grayscale facial images resized to a fixed resolution. Convolutional layers are used to extract spatial features, followed by activation functions such as ReLU to introduce non-linearity.

Pooling layers reduce spatial dimensions and improve generalization, while fully connected layers perform classification. The final output layer uses a softmax function to generate probability distributions across predefined emotional categories such as happiness, sadness, anger, and neutrality. The model is deployed using TensorFlow Lite for efficient on-device inference.

B. Text-Based Sentiment Analysis

The textual emotion analysis module processes user journal entries to determine sentiment polarity and emotional intensity. The input text is preprocessed through tokenization, normalization, and removal of irrelevant characters.

A lightweight sequence model is used to capture contextual relationships within the text. The output is a sentiment score ranging from negative to positive values, representing the emotional tone of the input. This module complements facial analysis by capturing contextual and cognitive aspects of emotion.

C. Multimodal Fusion Algorithm

The Affectoo system employs a late fusion strategy to combine outputs from the facial and textual models. Each model produces an emotion prediction along with a confidence score. These outputs are combined using a weighted decision mechanism.
The final emotional state is computed using a weighted function:

$$\text{Final Emotion} = w_f \times E_f + w_t \times E_t \qquad \text{Eq. 1}$$

where E_f represents facial emotion output, E_t represents textual emotion output, and w_f and w_t are dynamically assigned weights based on input reliability.

In cases of conflicting predictions, higher weight is assigned to the modality with greater confidence or contextual relevance. This approach improves robustness and reduces misclassification.

D. Procedural Game Adaptation Algorithm

The system incorporates a dynamic adaptation mechanism that modifies gameplay based on the user's emotional state. The detected emotion influences parameters such as game difficulty, visual elements, and interaction patterns.

For example, calming activities are triggered for high-stress states, while engaging cognitive tasks are introduced for neutral or low-energy states. This adaptive mechanism ensures that interventions are contextually relevant and effective.

E. Haptic Feedback Generation

To enhance user engagement, the system generates emotion-specific haptic feedback patterns. These patterns are designed using periodic signals synchronized with visual animations.

For instance, slow rhythmic vibrations are used for calming effects, while faster patterns are used for alertness. This multimodal feedback enhances immersion and reinforces emotional regulation techniques.

F. On-Device Deployment using TensorFlow Lite

All machine learning models are deployed on-device using TensorFlow Lite to ensure low latency and data privacy. The models are optimized through quantization techniques, reducing model size and improving inference speed.

Hardware acceleration is utilized through GPU or Neural Processing Units when available. This allows real-time processing without relying on cloud-based services, ensuring offline functionality and secure data handling.

VII. RESULTS AND DISCUSSION

The performance of the Affectoo system was evaluated based on real-time responsiveness, emotion detection capability, and user interaction experience. The system was tested on a standard mobile device under normal usage conditions to assess its practical feasibility.

The facial emotion recognition module demonstrated consistent performance under adequate lighting conditions, accurately identifying basic emotional expressions. The text-based sentiment analysis module effectively captured emotional tone from user journal entries, including variations in sentiment intensity.

The integration of multimodal inputs significantly improved the reliability of emotion detection. By combining facial and textual data, the system reduced incorrect predictions that typically occur in unimodal approaches. The fusion mechanism ensured that contextual information from text complemented visual cues, leading to more balanced and accurate emotional state estimation.

The system achieved low latency due to on-device processing using TensorFlow Lite. Emotion detection and response generation were performed in near real-time, ensuring a smooth and uninterrupted user experience. The absence of cloud dependency also enhanced data privacy and reduced network-related delays.

User interaction with the application demonstrated improved engagement compared to traditional static journaling systems. The 3D avatar provided intuitive visual feedback, reflecting the user's emotional state dynamically. Gamified intervention modules, such as guided breathing and interactive tasks, helped users remain engaged while promoting emotional regulation.

Sample outputs of the system, including user interface screens and avatar responses, are shown in Fig. 8.

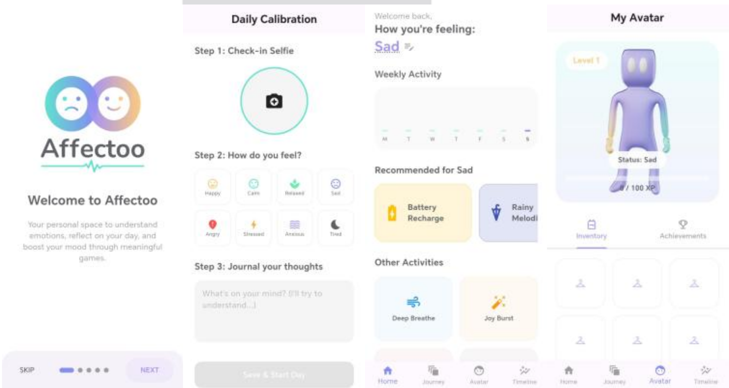

Fig. 8. User Interface of Affectoo Application

The avatar's emotional transitions based on detected mood states are illustrated in Fig. 9.

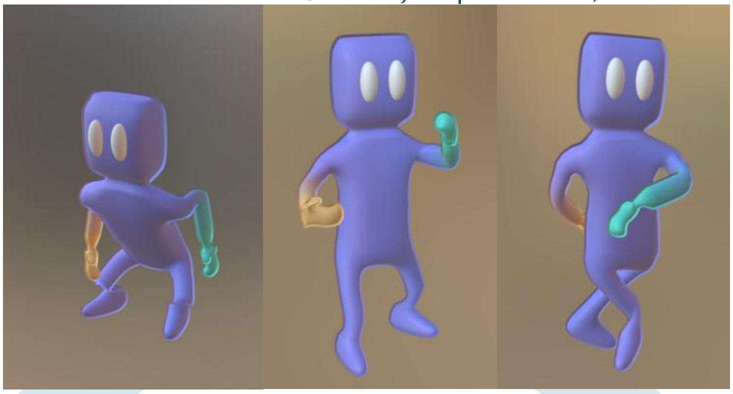

Fig. 9. 3D Avatar Emotional Response

Additionally, the gamified intervention module is shown in Fig. 10.

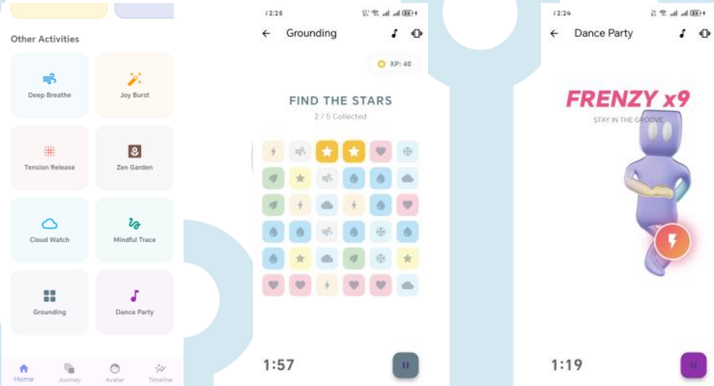

Fig. 10. Gamified Intervention Module

Overall, the results indicate that the Affectoo system provides an effective and engaging platform for real-time emotional self-regulation. The combination of multimodal emotion recognition, edge AI deployment, and gamified interaction contributes to improved usability, responsiveness, and user engagement.

VIII. Conclusion and Future Work

A. Conclusion

This paper presented Affectoo, a multimodal emotion-adaptive mobile system designed to support real-time emotional self-regulation. The system integrates facial expression recognition and text-based sentiment analysis to accurately estimate the user's emotional state. By leveraging on-device machine learning through TensorFlow Lite, the system ensures low latency, enhanced privacy, and offline functionality.

The incorporation of a multimodal fusion mechanism improves the reliability of emotion detection compared to unimodal approaches. Additionally, the use of gamified interventions and a responsive 3D avatar enhances user engagement and provides intuitive feedback for emotional awareness.

Overall, Affectoo demonstrates a scalable and user-centric approach to mental wellness technology by combining affective computing, edge AI, and interactive design within a unified mobile platform.

B. Future Work

Future enhancements to the system can focus on expanding the range of input modalities by integrating physiological signals such as heart rate variability (HRV) and galvanic skin response (GSR) through wearable devices. This would further improve the accuracy and depth of emotion recognition.

The incorporation of lightweight, on-device conversational agents using advanced language models can enable more personalized and empathetic user interaction. Additionally, expanding the library of gamified interventions and customizable 3D environments can enhance user experience and long-term engagement.

Further research can also include large-scale user studies to evaluate the effectiveness of the system in real-world scenarios. These studies can provide insights into user behavior and help refine the intervention strategies for improved emotional well-being outcomes.

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