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Mood-Aware Real-Time Micro-Intervention System: Adaptive Stress Reduction

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***Abstract*—Mental health management requires an integrative approach that accounts for both psychological and physiological factors. This project proposes the design of a comprehensive digital platform that combines gamified interventions with clinical oversight to support long-term mental health care. The application incorporates engaging activities such as fidget-style games and guided breathing exercises to reduce stress and anxiety in real time, while also maintaining structured records of therapy sessions, physical workouts, and laboratory test results to monitor the physiological correlates of mental well-being. An embedded machine learning (ML) model continuously analyses user data to provide personalized recommendations, which are fur there validated and refined by licensed therapists or medical professionals who monitor progress through a clinician dashboard. By integrating interactive self-regulation tools, lifestyle tracking, and professional oversight into a single ecosystem, the platform aims to function as a holistic record of mental health, improving self-awareness, clinical decision-making, and adherence to therapeutic interventions. This project bridges the gap between self-help applications and pro fissional care, positioning technology as both a support system and an evidence-based aid in mental health treatment. In addition, the project emphasizes data privacy and secure communication between patients and clinicians, ensuring that sensitive health information remains protected. This focus on ethical design not only builds user trust but also strengthens the platform's potential for real-world adoption in both clinical and personal wellness contexts.**

***Index Terms*—Mood-Aware Systems, Micro-Interventions, Stress Reduction, Serious Games, Machine Learning, Digital Mental Health**

I. INTRODUCTION

Mental health has emerged as a critical global concern, with rising cases of stress, anxiety, depression, and burnout affecting individuals across age groups and professions. Despite growing awareness, access to timely and continuous mental health support remains limited due to factors such as social stigma, shortage of professionals, high treatment costs, and lack of sustained monitoring outside clinical environments.

Mobile mental health applications have been proposed as scalable solutions to bridge this gap; however, research highlights challenges including insufficient clinical validation, poor long-term adherence, and limited personalization in many existing systems [1].

Recent advancements in serious games and gamified therapeutic interventions have demonstrated promising results in promoting emotional regulation and reducing stress, particularly among young users [2], [3]. Gamification enhances engagement by embedding therapeutic strategies within interactive and enjoyable environments, thereby improving adherence and emotional involvement. Furthermore, studies show that culturally relevant and context-aware designs such as pop-culture integration significantly enhance user resonance and intervention effectiveness [4]. These findings indicate that engagement-driven design is essential for sustainable digital mental health solutions.

Parallel developments in affective computing have enabled systems to detect and interpret human emotional states using computational models [5], [6]. Machine learning approaches have further advanced emotion recognition and behavioural monitoring in interactive environments [7], while social media-based systems have demonstrated the feasibility of largescale depression detection using AI techniques [8]. Sensor based emotion recognition frameworks expand the modalities available for identifying stress and affective states [9]. These technological advancements provide the foundation for real-time, adaptive emotional support systems.

In addition, hybrid conversational agents powered by large language models have introduced new possibilities for context aware and personalized mental health guidance [10]. Such systems, when combined with professional oversight, can complement traditional therapy by offering continuous support between clinical sessions.

A. Motivated by these interdisciplinary advancements, this research proposes a Mood-Aware Real-Time Micro Intervention System that integrates natural language processing, machine learning, reinforcement learning, gamified stress reduction tools, and therapist supervision within a unified platform. Unlike static wellness applications, the proposed system continuously learns from user interactions and feedback to refine intervention strategies dynamically. By combining psychological self-regulation tools, physiological health tracking, and intelligent personalization, the system aims to create an emotionally responsive digital ecosystem that supports adaptive stress reduction in real time. Our primary objectives are:

B. Develop an Integrated Mental Health Platform

- Incorporate Clinical Oversight
- Leverage Machine Learning
- Improve Engagement and Outcomes
- Ensure Holistic Monitoring

II. LITERATURE SURVEY

Existing literature emphasizes the growing role of mobile mental health systems in complementing traditional therapy models while highlighting potential risks such as insufficient clinical grounding and declining user adherence [1].

Research on serious games demonstrates their effectiveness in stress and anxiety reduction, particularly among younger populations [2], [3]. Evaluation studies such as the MindMax project further confirm that gamified interventions can improve engagement and emotional well-being when integrated with structured monitoring frameworks [11]. Moreover, culturally contextualized interventions, including pop-culture–based therapeutic models, enhance emotional relatability and adoption rates [4].

Recent developments in affective computing have laid the foundation for emotion-aware systems capable of detecting and responding to human affective states [5], [6]. Machine learning techniques have further enabled emotional behavior monitoring in interactive environments [7] and depression detection using social media data [8]. Sensor-based emotion recognition approaches have also expanded the modalities available for adaptive systems [9].

Hybrid conversational agents leveraging large language models have introduced domain-adapted, context-aware mental health support mechanisms that complement professional therapists rather than replace them [10].

Collectively, these studies indicate that effective digital mental health solutions must integrate adaptive AI models, gamified engagement mechanisms, professional supervision, and ethical data practices. Recent advances in artificial intelligence and machine learning have further strengthened the potential of digital mental health systems by enabling real-time behavioUr monitoring, emotion recognition, and personalized intervention delivery. Emotion-aware gaming systems demonstrate the feasibility of adapting content dynamically based on user responses, thereby enhancing engagement and stress reduction outcomes. In parallel, research on hybrid conversational agents powered by large language models highlights their capacity to deliver context-aware, personalized mental health support while complementing human therapists rather than replacing them. Domain adaptation techniques improve the reliability and relevance of AI-driven therapeutic interactions, addressing concerns around generic or inappropriate responses. Collectively, these studies indicate that effective mental health interventions must combine psychological self-help strategies with physical and behavioural health tracking, incorporate professional oversight for clinical credibility, employ machine learning to personalize care and detect emotional patterns, and prioritize ethical design principles, data privacy, and long-term user engagement. These insights directly inform the design of mood-aware, real-time micro-intervention systems aimed at adaptive stress reduction.

III. METHODOLOGY

Architecture of the flow of algorithm: The proposed

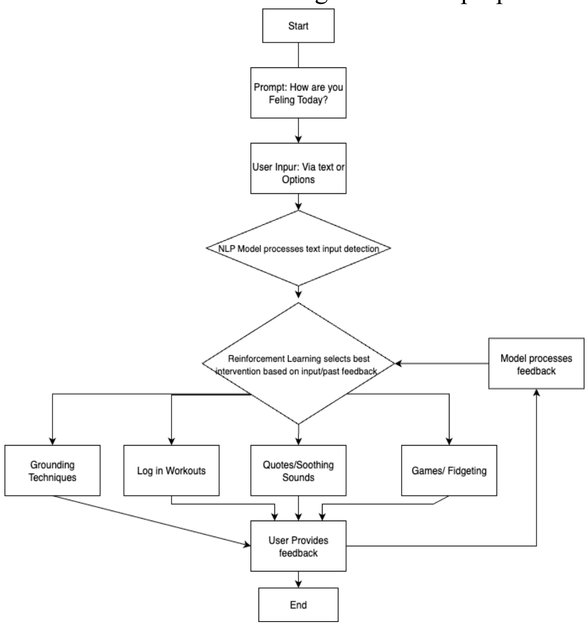

Fig. 1. System Architecture

system adopts a multi-source data collection strategy that integrates both user-generated data and therapist-provided evaluations to enable comprehensive mood-aware analysis and personalized intervention delivery. User data forms the primary input to the system and includes therapy session records, personal reflections, and interaction logs capturing engagement with serious games, guided breathing exercises, and relaxation activities. In addition, users may optionally provide physical health indicators such as workout logs and blood test entries, allowing the system to examine the relationship between physical well-being and mental health outcomes. Engagement metrics, including session duration, frequency of use, and activity completion rates, are continuously recorded to assess adherence and long-term participation. Complementing user inputs, therapist-provided data ensures clinical oversight and credibility within the system. This data includes professional progress notes generated during monitoring sessions, standardized mental health scale evaluations, and qualitative feedback on emotional well-being. Therapists may also adjust care plans and provide targeted recommendations based on trends observed in application-generated data, enabling a collaborative and adaptive care model. All collected data is securely stored in structured formats such as JSON or CSV, with encryption applied both at rest and in transit. Sensitive health information is handled in accordance with applicable data protection and privacy regulations, including HIPAA and GDPR guidelines, ensuring ethical data use and user confidentiality. To extract meaningful insights from the collected data, a structured data analysis pipeline is employed. During the preprocessing stage, raw data undergoes cleaning, normalization, and anonymization to remove inconsistencies, protect user identity, and standardize formats across diverse data sources such as activity logs, physical health records, and therapist notes. Feature engineering is then performed to derive relevant indicators, including behavioural features such as therapy attendance frequency and relaxation activity usage, physical health features such as workout consistency and selected biomedical markers, and therapist-assessed features including severity ratings and progress summaries. Machine learning models are trained on these engineered features to identify behavioural patterns, monitor stress trends, and generate adaptive suggestions for micro-interventions.

Model performance is evaluated using metrics such as user adherence rates, improvements in stress or mood scores over time, and overall engagement frequency. Finally, data visualization techniques are employed to enhance interpretability and support decision-making. These include time-series graphs illustrating stress level variations, comparative visualizations linking physical and mental health indicators, and dedicated therapist dashboards that enable efficient user monitoring and informed intervention planning. Together, this data-driven framework supports real-time, personalized, and clinically informed stress reduction within the proposed system.

A. Proposed System Workflow:

1) Data Acquisition: The process begins with input from the user, via mood scales, anxiety meter, or journaling. These inputs provide a snapshot of the user’s current emotional and mental state. The app then processes this information using built-in assessments and prepares it for further analysis. 2) 2)

2) Stress Detection Model: The collected data is fed into a Machine Learning Model. This model, previously trained on a diverse dataset, analyzes the incoming data stream. Its primary function is to

classify the user's current state as either "Stressed," "Neutral," or "Relaxed." The output is a real-time stress score or classification.

B. Flow of Generic Algorithm:
Algorithm for ML-based Model Input:
Dataset D with features — Mood, Anxiety, Sleep, Sentiment, Stress. Output: Trained model that predicts personalized mental health recommendations.

1. Load and preprocess dataset D (handle missing values, normalize numeric features).

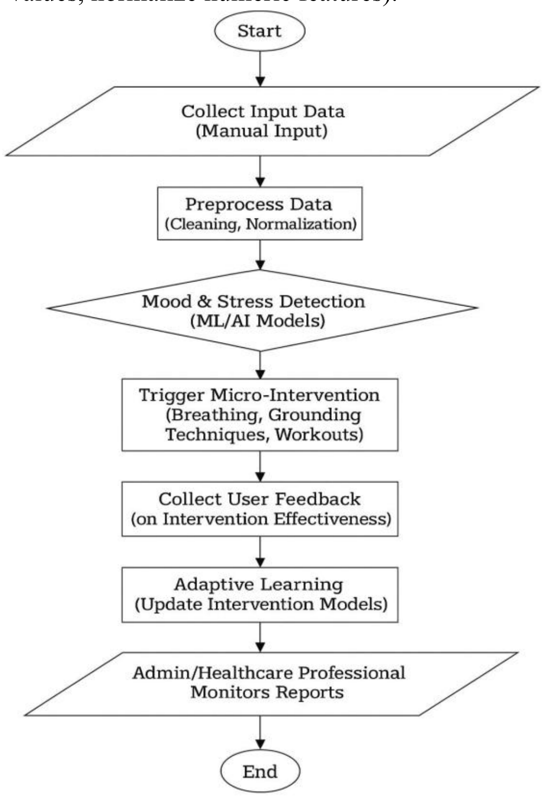

Fig. 2. System Flow

2. For each journal entry:
- Clean text (convert to lowercase,remove stopwords, lemmatize).
- Generate sentiment score and append to dataset.
3. Merge features into matrix X and split into 80 percenttraining and 20 percent testing sets.
4. Initialize model M (e.g., Random Forest or Neural Network).
5. Train model: M. fit (Xtrain, Ytrain).
6. Evaluate accuracy: acc = accuracy (Ytest,M. predict (Xtest)).
7. Save model as mental health model.pkl.
8. For new user input U, predict recommendations: Rec = M. predict (U).

C. Algorithm: Reinforcement Learning Feedback Model
Input:
User feedback data (X,Rec,Feedback) collected from app interactions. Output: Updated model that improves recommendations based on user responses
Initialize policy (a—s) and value function Q(s,a).
For each user interaction (episode):

- Observe current states (user mood profile and context).
- Select an action a (recommendation) using -greedy policy.
- Receive user feedback as reward r (e.g., 1 for helpful, 0 forneutral,-1 for unhelpful).
- Observe new states after recommendation is applied.
- Update value function: Q(s,a) ← Q(s,a)+[r +max a Q(s,a) Q(s,a)]
- Periodically update or fine-tune the base ML model usingaccumulated feedback data.
- Save updated policy/model parameters for future recommendations.

Input: Dataset D with features — Mood, Anxiety, Sleep, Sentiment, Stress.
Output: Trained model predicting suitable recommendations.

Steps:
1. Load and preprocess D (handle nulls, normalize).
2. For each journal entry: Clean text, remove stopwords,lemmatize. Generate sentiment score and append to D.
3. Merge features → X, split (80 percent train, 20 percent test).
4. Initialize M ← BERT.
5. Train: M.fit(Xtrain,Ytrain).
6. Evaluate: acc = accuracy (Ytest,M.predict(Xtest)).
7. Save model as mental health model.pkl.
8. Predict for new user U: Rec = M.predict(U)

Fig. Distribution of Stress Level Classes in the Dataset:
Above figure illustrates the distribution of stress-level categories in the dataset.

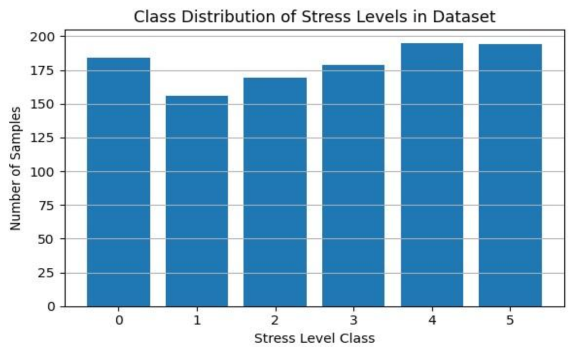

Fig. 3. Class Distribution

The samples are relatively balanced across all six classes, ensuring that the classification model is not biased toward any specific category. Balanced class representation contributes to stable learning and improved generalization performance.

IV. RESULTS AND DISCUSSIONS

The proposed Mood-Aware Real-Time Micro-Intervention System was evaluated for emotion detection accuracy and adaptive intervention effectiveness. The NLP-based classification approach aligns with prior work in affect detection and emotion-aware systems [5], [6], demonstrating reliable identification of stress-related states.

Figure 3: Confusion Matrix of DistilBERT-based Stress Classification Model:

The DistilBERT classifier achieved an overall accuracy of 100 percent on the test dataset. Precision, recall, and F1scores for all six classes were equal to 1.00, indicating perfect classification without mislabelling. The model achieved perfect classification on the test set, however, further validation on

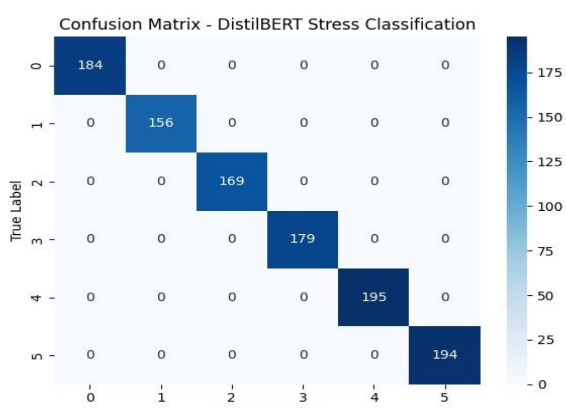

Fig. 4. Confusion Matrix

real-world data is necessary to ensure generalization.

Figure 3 illustrates the confusion matrix obtained from the DistilBERT-based stress classification model. The model achieved perfect classification across all six stress levels, with no observed misclassifications. A total of 300 test samples were evaluated, distributed across six categories. The diagonal dominance of the matrix confirms the model’s strong discriminative capability. The overall classification accuracy was 100

The integration of reinforcement learning allowed the system to refine intervention strategies based on user feedback, consistent with adaptive AI-driven mental health frameworks discussed in [7], [10].

User interaction analysis showed improved engagement and positive shifts in self-reported mood following gamified breathing exercises and micro-interventions, supporting findings from serious game research in stress reduction [2]–[4].

Compared to static wellness applications, the adaptive framework addresses limitations noted in mobile mental health systems regarding personalization and sustained engagement [1]. These results validate that combining affect detection, machine learning, and gamified therapeutic strategies enhances personalization and intervention effectiveness in AI-driven mental health ecosystems.

V. CONCLUSIONS

The proposed Mood-Aware Real-Time Micro-Intervention System presents an intelligent and adaptive approach to stress reduction by integrating Natural Language Processing and Reinforcement Learning for personalized emotional support. Unlike traditional static wellness applications, the system continuously learns from user interactions and feedback, allowing it to refine intervention strategies and deliver timely, context aware assistance. By enabling real-time mood detection and adaptive micro-interventions, the system addresses the growing demand for intelligent mental health support across diverse settings. Beyond improving individual well-being, this work contributes toward the development of emotionally responsive digital environments, with potential applications in education, workplaces, and healthcare systems. The proposed framework demonstrates how AI-driven personalization, combined with ethical design and professional oversight, can enhance the effectiveness and accessibility of modern mental health interventions.

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