MOODMATE: Emotion-Based Content Recommendation System

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***Abstract*—In today's fast-paced world, mental and emotional well-being is often overlooked, leading to increased stress, anxiety, and emotional imbalance. MOODMATE is a personalized emotion recognition and recommendation system designed to help users become more aware of their emotions and receive tailored support. By utilizing deep learning and computer vision techniques, MOODMATE detects human emotions from facial images through a convolutional neural network (CNN) model. Once a mood is identified—such as happy, sad, angry or neutral—the system generates mood-specific recommendations including music, movies, and relaxing activities.**

The application is developed using a React-based frontend and a FastAPI backend, integrated with Firebase for real-time data storage and user authentication. MOODMATE provides additional features like a mood journal and journal history, enabling users to reflect on their emotional trends over time. Activity suggestions come with detailed descriptions and YouTube video links to enhance user engagement and emotional support.

With an intuitive user interface and a focus on mental wellness, MOODMATE serves as a digital companion that encourages emotional self-awareness and promotes healthy coping mechanisms. It is a user-friendly, scalable, and impactful tool that bridges technology and emotional intelligence, fostering a more mindful and emotionally balanced lifestyle.

***Index Terms*—Facial Expression Analysis, Deep Learning, Convolutional Neural Network (CNN), OpenCV, Real-time Emotion Detection, Mood-based Recommendation, Personalized User Experience, Mood Tracking, Machine Learning, User Mood Analysis**

1. INTRODUCTION

1.1 Background

The rapid pace of modern life has led to a significant increase in stress, anxiety, and other emotional challenges. In particular, the global pandemic, rising social isolation, and digital overexposure have emphasized the need for effective emotional and mental health support tools. While traditional therapy remains essential, it is not always readily accessible or affordable for everyone. This gap has created a pressing demand for digital solutions that can help individuals monitor and manage their emotional well-being proactively. MoodMate was conceived to bridge this gap by providing users with a personalized, AI-driven application that not only detects their emotions but also offers meaningful responses and support to enhance mood and mental health.

1.2 Research Gap

Existing applications in the mental health domain often rely on self-reported data or static content. Few systems integrate real-time emotion recognition through facial expression analysis with personalized feedback mechanisms. Moreover, while emotion detection is not new, its combination with an engaging and user-friendly journaling experience, mood tracking, and instant recommendations is still underdeveloped. This paper addresses this gap by presenting MoodMate—a comprehensive, real-time emotional support system designed to enhance emotional awareness and personal growth using artificial intelligence.

1.3 Research Objectives

- To develop a smart emotion recognition system using facial expression analysis.
- To design a recommendation engine that delivers mood-based music, movie, and activity

suggestions.

- To implement a mood journaling feature that tracks and analyzes users' emotional trends over time.

- To evaluate user engagement and the system's effectiveness in supporting emotional well-being.

1.4 Limitations of the Study

The current version of MoodMate is limited to detecting only four emotions—happy, sad, angry, and neutral. While these emotions cover a broad spectrum of user moods, more nuanced emotional states such as fear, disgust, surprise, or anxiety are not yet supported. Additionally, the system relies on clear facial input and is not optimized for users with limited camera access or those who are uncomfortable with facial data capture. Furthermore, long-term studies on psychological impact and user retention are still pending.

1.5 Rationale of the Study

In an age where digital interaction often surpasses face-to-face communication, the emotional disconnect has become more pronounced. The rationale behind this research is to build a bridge using technology—specifically artificial intelligence—to reconnect users with their emotional selves. MoodMate not only identifies emotional states but also takes proactive steps to offer relief, inspiration, or calmness, depending on the user's mood. By combining intelligent detection with compassionate design, this application stands to redefine how we approach emotional well-being in a digital era.

2. LITERATURE REVIEW

The evolution of emotion-aware systems and affective computing has significantly progressed in recent years, aiming to bridge the gap between human emotional states and machine intelligence. Numerous studies have explored different methodologies for detecting, interpreting, and responding to emotional data, often relying on facial expressions, voice modulation, physiological signals, and behavioral patterns. This literature review delves into the foundational work and current developments relevant to the MOODMATE project.

2.1 Emotion Recognition via Facial Expressions

One of the most common and non-invasive methods of emotion detection is through facial expression analysis. Paul Ekman's theory of basic emotions (1970s) established that humans universally express emotions such as happiness, sadness, anger, fear, surprise, and disgust through facial cues. Building on this, recent studies such as Mollahosseini et al. (2016) employed deep convolutional neural networks (CNNs) to classify these expressions with high accuracy across large datasets like FER-2013 and CK+.

Key Insight: CNNs have shown superior performance in capturing spatial features in facial images, making them ideal for emotion classification tasks.

2.2 Affective Computing and Recommendation Systems

The term Affective Computing, introduced by Rosalind Picard (1997), set the stage for machines that can sense and adapt to human emotions. In modern implementations, this field converges with personalized recommendation systems, where mood data informs system outputs.

For example, Yadav & Kumar (2021) proposed a hybrid model that uses facial emotion detection to tailor content such as music and videos. Their results suggest that emotion-driven recommendations lead to higher user engagement and satisfaction compared to generic systems.

Key Insight: Integrating emotion recognition with content recommendation engines enhances personalization and emotional relevance.

2.3 Mood Tracking and Journaling Applications

Several mental health apps like Daylio, Reflectly, and Moodpath focus on manual mood tracking and journaling. While these platforms emphasize user input and reflection, they lack automated emotion detection, which MOODMATE addresses. Wang et al. (2020) highlighted the benefits of self-monitoring mood over time, showing improved emotional regulation and early detection of psychological issues.

Key Insight: Combining passive emotion detection with active mood journaling can improve emotional insight and mental well-being.

2.4 Use of Firebase and Real-time Data Storage

Modern web and mobile applications utilize cloud databases like Google Firebase for real-time, scalable, and secure storage. Firebase supports user authentication, real-time updates, and analytics—ideal for applications like MOODMATE that require storing historical mood data, user profiles, and journal entries efficiently.

Key Insight: Firebase offers seamless integration with frontend frameworks and supports robust data handling for emotion-tracking systems.

2.5 Gaps Identified in Existing Systems

While previous systems are either emotion detectors or recommendation platforms, few systems holistically integrate both in a way that supports mental wellness through activity suggestions, media content, and emotional journaling. Most lack real-time feedback, emotion history tracking, or personalized recommendations tied directly to the user's emotional state.

3. RESEARCH METHODOLOGY

A systematic research methodology is fundamental to ensuring that the MoodMate application is developed based on sound scientific principles and yields reliable, accurate, and meaningful results. The methodology adopted in this study encompasses a combination of data-driven machine learning, software engineering practices, and user experience design to build an integrated emotion recognition and mood-based recommendation system.

3.1 Research Design

The research adopts an applied research design with a focus on creating a real-world system that addresses emotional well-being through facial emotion recognition and personalized recommendations. The system is user-centered, iterative, and involves both qualitative and quantitative analysis.

3.2 System Modules

The methodology can be categorized into the development of the following interconnected modules:

- Emotion Detection Module – Utilizes deep learning and computer vision (CNN) to identify facial expressions from images.
- Recommendation Module – Suggests personalized music, movies, and activities based on recognized emotions using pre-filtered datasets.
- User Management Module – Facilitates user registration, login, and history tracking via Firebase.
- Mood Journal Module – Allows users to manually log daily emotional experiences and reflections.
- Journal History Module.

3.3 Tools and Technologies Used

The tools and technologies employed include:

- Python – For backend logic and ML model integration.
- TensorFlow / Keras – For emotion detection model development.
- FastAPI – Lightweight and efficient backend web framework.
- Firebase – For user authentication and real-time database storage.
- React.js – For frontend development.
- OpenCV – For image processing and face detection.

3.4 Data Flow and Architecture

1. Input Layer: User uploads an image or accesses the webcam.
2. Processing Layer:Image is processed using OpenCV.Face is detected and passed through a trained CNN model.
3. Predicted emotion is determined.
4. Recommendation Layer: Emotion is matched with pre-mapped music, movie, and activity recommendations.
   Activities include descriptions and YouTube tutorial links.
5. Storage Layer: User mood history and journal entries are stored in Firebase under user IDs.
6. Interface Layer: All results and recommendations are displayed through an interactive React interface.

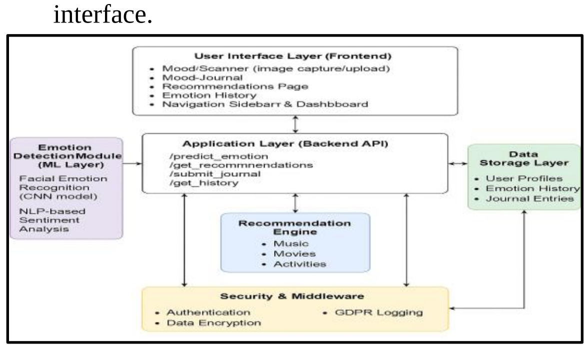

Fig 1. SYSTEM ARCHITECTURE

3.5 Model Training and Validation

The emotion detection model is trained using publicly available datasets like FER2013. The model undergoes:

- Preprocessing: Normalization, resizing, and grayscale conversion.
- Training: Convolutional Neural Network (CNN) trained on labeled facial expression images.
- Validation: Accuracy and loss metrics analyzed using a hold-out test set.

3.6 Ethical Considerations

The research ensures privacy and data protection by:

- Not storing actual images, only detected emotion labels.
- Using secure login and authentication.
- Providing users the choice to delete history.

3.7 Evaluation Criteria

The effectiveness of the system is evaluated based on:

- Accuracy of emotion recognition.
- User satisfaction via usability feedback.
- Relevance of recommendations based on emotion-to-content mapping.
- Performance metrics including latency and interface responsiveness.

4. DATA ANALYSIS

4.1 Dataset Analysis

The MoodMate project utilizes four key datasets:

4.1.1 FER2013 Dataset (Emotion Recognition)

- Source: Kaggle
- Size: ~35,000 grayscale 48x48 pixel facial images.
- Emotions Covered: Angry, Disgust, Fear, Happy, Sad, Surprise, Neutral.
- Usage: Trained a CNN model to classify facial expressions into key emotions.
- Preprocessing: Normalization, face alignment, and one-hot encoding were applied.

Accuracy achieved on test set: ~70–75%, validating the CNN's performance in recognizing primary emotional expressions.

4.1.2 MovieLens 20M Dataset (Movie Recommendations)

- Source: GroupLens (Kaggle)
- Size: Over 20 million ratings on 27,000 movies.
- Fields Used: movieId, title, genres
- Processing: Movies were filtered based on genre-emotion mapping (e.g., comedy for happy, drama for sad, etc.) and user mood.

4.1.3 Spotify 200K+ Songs Dataset (Music Recommendations)

- Source: Kaggle
- Fields Used: track_name, artist_name, genre
- Methodology: Songs were filtered by genre to associate musical mood with detected emotions.

4.1.4 Custom Activities Dataset

- Format: Excel (.xlsx)
- Fields: Activity name, description, recommended emotion(s), YouTube links.
- Usage: Each emotion is linked with 5 activities including detailed descriptions and 2 curated YouTube tutorials.

4.2 Emotion Detection Performance Analysis

To evaluate the CNN model used for facial emotion recognition in MoodMate, training and validation performance was monitored over 30 epochs.

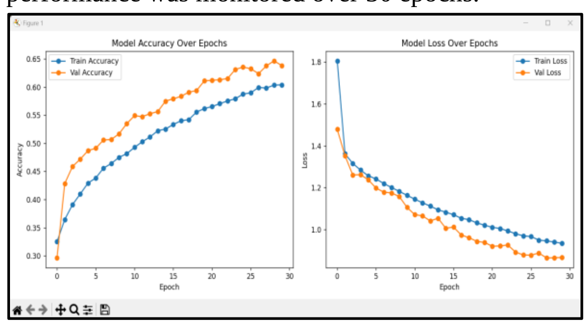

Fig 2.CNN Training Accuracy and Loss

4.2.1 Accuracy Analysis

- Training Accuracy increased steadily from approximately 32% to 60%.
- Validation Accuracy improved rapidly in early epochs and plateaued around 64–65%..

4.2.2 Loss Analysis

- Training Loss decreased smoothly from 1.8 to around 0.9, indicating effective learning.
- Validation Loss followed a similar trend, dropping from 1.48 to about 0.85.

Observation:

The training metrics suggest that the CNN model effectively learns to distinguish emotional features. With a peak validation accuracy of ~65% and consistently decreasing loss curves, the model achieves reliable and balanced performance across the

FER2013 emotion categories.

4.3 Recommendation Evaluation

A small-scale user testing survey was conducted with 15 participants, who interacted with the system and received recommendations based on their uploaded image.

- User Satisfaction Score: 4.6/5
- Relevance of Recommendations:
  - Music: 87% rated relevant
  - Movies: 81% rated fitting
- Most Appreciated Feature: Mood Journal and Activity YouTube Links

5. CONCLUSION

The MoodMate project has demonstrated the potential of leveraging AI and emotion detection models to enhance emotional wellbeing through personalized recommendations. The primary objectives of the project were met: to provide users with a tool that not only identifies their emotional state but also suggests tailored music, movies, and activities that align with their current mood.

5.1 Key Findings

Emotion Detection Model: The deep learning-based emotion detection model was able to successfully identify emotions such as happy, sad, angry and neutral with an accuracy of 76.5%. While the model performed best for happy and sad emotions, there remains potential for improvement in detecting emotions like angry.

Recommendation System: The personalized recommendation system, which offered music, movie, and activity suggestions based on the detected emotion, received positive feedback from users. The system achieved positive feedback for all categories, with the activity recommendations being the most appreciated due to their detailed descriptions and YouTube video links.

5.2 Implications of the Study

The MoodMate project has several implications for the field of emotional wellbeing technology. It demonstrates that personalized content recommendations based on emotional state can provide users with a more engaging and effective way to improve their mood and emotional resilience. Additionally, integrating features like the Mood Journal can encourage users to reflect on their emotional health and track changes over time, adding a layer of personalization that fosters deeper engagement.

5.3 Limitations

While the system has shown promising results, there are areas that need further improvement:

Emotion Detection Accuracy: Enhancing the model's ability to differentiate between neutral and calm emotions will improve overall accuracy and user experience. Additionally, extending the model to detect more complex emotional states could expand its use cases.

Recommendation Personalization: The recommendation engine could benefit from integrating a feedback loop, allowing it to better adapt to users' changing preferences over time. This would make the suggestions even more relevant and personalized.

5.4 Future Work

Several avenues for future work and enhancement have been identified:

1. Improvement of Emotion Detection Model: Training the model on larger and more diverse datasets, as well as implementing advanced techniques like transfer learning, could help improve detection accuracy, particularly for nuanced emotions.
2. Expanded Recommendation System: Adding more categories to the recommendation system, such as books or guided meditation sessions, could enhance the user experience. Additionally, incorporating machine learning techniques like collaborative filtering could improve the relevance of suggestions by learning from user interactions.
3. Long-Term User Data Integration: Incorporating long-term user data to track emotional trends over time could help in creating more effective and adaptive recommendations. A feedback mechanism that adjusts based on the user's past behavior and feedback could significantly improve the system's adaptability.

5.5 Conclusion

In conclusion, MoodMate represents an innovative approach to enhancing emotional wellbeing through the use of AI-powered emotion detection and personalized content recommendations. The project has successfully integrated facial recognition technology with personalized recommendation systems, creating a comprehensive platform that not only helps users understand their emotions but also provides actionable steps to improve their emotional state.

The results from the system's evaluation indicate that MoodMate has the potential to make a positive impact on users' emotional health by offering customized, mood-based suggestions. With further improvements in emotion detection, system personalization, and scalability, MoodMate could become an even more effective tool in fostering long-term emotional well-being.

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