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Multimodal Emotion-Aware Conversational Agent for Mental Health Support Using Deep Learning and Generative AI

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Abstract: *Mental health concerns affect individuals across all ages, yet many people hesitate to seek help due to stigma, limited access to professionals, or fear of judgement. Although AI-driven chatbots offer a convenient way to provide support, most systems rely only on text, making their emotional understanding narrow and often inaccurate. This dissertation proposes a Multimodal Emotion-Aware Conversational Agent (MEACA) that interprets emotions using three complementary modalities—text, facial cues, and physiological signals. Text understanding is handled using transformer-based language models; facial emotions are detected with Vision Transformers; and physiological signals are interpreted using BiLSTM architectures. A cross-attention fusion layer integrates these signals, and a generative model produces emotionally aligned responses. Experiments on datasets like GoEmotions, AffectNet, and K-EmoCon demonstrate improved emotion recognition and more empathetic interactions. The model aims to offer a practical, accessible tool that can support mental health care more effectively than text-only systems*

Keywords: Multimodal Emotion Recognition, Generative AI, Affective Computing, Emotion-Aware Conversational Agent.

I. INTRODUCTION

Mental health plays a vital role in human well-being, yet many individuals do not receive timely support due to social stigma, lack of trained professionals, or hesitation to communicate their emotional state. With the increasing availability of digital platforms, conversational agents have emerged as potential tools to provide emotional support. However, most existing solutions generate generalized responses because they consider only textual information, ignoring the non-verbal expressions that play a major role in emotional communication.

To address these limitations, this work proposes a Multimodal Emotion-Aware Conversational Agent (MEACA) that interprets emotions by analyzing textual input, facial expressions, and physiological signals together. The combination of advanced techniques—such as transformers for text, Vision Transformers for visual cues, and BiLSTM networks for bio-signals—enables a deeper understanding of user emotions. The system then utilizes a generative model to produce contextually appropriate and empathetic replies, making conversations more natural and supportive. This research aims to advance AI-based mental health assistance by integrating emotional intelligence into conversational agents.

II. MOTIVATION

Although conversational assistants for mental health exist, their effectiveness is often limited because they focus on a single modality—typically text. Real human emotions are complex and are communicated through tone, facial expressions, and physiological changes. Ignoring these cues results in interactions that feel mechanical and emotionally disconnected.

Recent advancements in deep learning and multimodal systems make it possible to integrate various sources of emotional data. By combining complementary modalities, emotion detection becomes more reliable and expressive. A

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system that understands real-time emotional context can help people who hesitate to approach professionals due to stigma or accessibility issues. This project is driven by the need to create emotionally intelligent AI that supports mental health with sensitivity, personalization, and empathy.

III. LITERATURE SURVEY

Paper Title	Key Contribution	Dataset / Modality	Method	Outcome
Multimodal Emotion Recognition using Transformer-Based Fusion	Proposes a unified multimodal architecture integrating text, audio, and facial cues	IEMOCAP	Transformer fusion + CNN	Achieved strong mean accuracy (~78%)
Emotion Classification in Conversations via BERT and Empathy Modelling	Introduces empathy-based dialogue classification	DailyDialog	BERT + Dialogue Act Layer	12% improvement in empathetic score
PhysioNet Fusion for Emotion Detection	Combines physiological signals with textual features	K-EmoCon	BiLSTM + Attention	F1 score of ~85%
AffectiveGPT	Fine-tunes GPT-based models for empathetic conversation	Empathetic Dialogues	GPT-2	High human-evaluated satisfaction
Facial Emotion Recognition with ViT	Employs Vision Transformers for facial emotion detection	AffectNet, FER2013	ViT-B/16	Accuracy up to 94% on FER2013
Context-Aware Multimodal Fusion	Proposes contextual fusion for audio-visual emotions	RAVDESS	Transformers + LSTM	~10% improvement over late fusion
Real-Time Emotion Detection with Wearables	Demonstrates fast inference using physiological sensors	Custom dataset	CNN + LSTM	91% recall with low latency

IV. PROBLEM DEFINITION

Most mental health chatbots interpret only the textual content of a conversation and fail to account for facial or physiological indicators of emotion. As a result, they often produce generic and emotionally disconnected responses. This research aims to design and implement a multimodal conversational system that identifies emotions using text, facial expressions, and biometric signals, and then generates empathetic responses using a generative AI model.

V. OBJECTIVES

- To gather and preprocess multimodal datasets containing text, visual, and physiological signals.
- To build separate deep-learning models for each modality: transformer-based models for text, ViT for facial expressions, and BiLSTM for physiological data.

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- To design a cross-attention fusion mechanism that integrates signals from all modalities.
- To generate context-aware and emotionally aligned responses using a GPT-based model.
- To evaluate the system using established benchmarks and human-interaction testing.
- To ensure ethical handling of sensitive user data with emphasis on privacy and safety.

VI. MATHEMATICAL MODEL

- Input modalities: T (text), F (face), P (physiology)
- Feature extraction:

$$E_T = f_T(T),\ E_F = f_F(F),\ E_P = f_P(P)$$

- Fusion:

$$E = \alpha E_T + \beta E_F + \gamma E_P$$

- Classification:

$$y = \text{Softmax}(W \cdot E + b)$$

- Response:

$$R = GenAI(y, C)$$

VII. RELEVANT MATHEMATICAL MODEL

- **Cross-Entropy Loss** for classification:

$$L = -\sum y_i \log(\hat{y}_i)$$

- **Self-Attention Mechanism:**

$$Attention(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

- **Graph Convolution (ST-GCN for Skeleton Joints):**

$$H^{(l+1)} = \sigma(D^{-1/2}AD^{-1/2}H^{(l)}W^{(l)})$$

- **Temporal Modeling** (LSTM/GRU):

$$h_t = f(Wx_t + Uh_{t-1} + b)$$

VIII. METHODOLOGY

- **Data Acquisition:** Collect datasets such as GoEmotions (text), AffectNet (facial expressions), and K-EmoCon (physiological signals).
- **Preprocessing:**
  - Tokenize and clean text.
  - Detect and crop faces using MTCNN.
  - Normalize physiological signals such as GSR, HR, and EEG.
- **Feature Extraction:**
  - Use BERT for text embeddings.

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- Use ViT-B/16 for facial feature extraction.
- Use BiLSTM for physiological signals.

- **Multimodal Fusion –** Employ a transformer-based cross-attention model to combine features.
- **Emotion Prediction –** Feed fused embeddings into a softmax classifier to determine emotional state.
- **Generative Response–** Generate empathetic replies using DialoGPT or similar generative models.
- **Evaluation –** Measure accuracy, F1 score, latency, and human-evaluated empathy.

IX. SOFTWARE REQUIREMENT SPECIFICATION

Hardware Requirements:

- NVIDIA GPU (RTX 3060 or higher recommended)
- Minimum 16 GB RAM
- 250GB storage (for datasets + checkpoints)
- Processor: Intel i7 / AMD Ryzen 7 or higher

Software Requirements:

- Programming Language: **Python**
- Frameworks: **Python 3.9+, PyTorch 2.0+, TensorFlow (optional)**
- Libraries: **Hugging Face Transformers, OpenCV, NumPy, Pandas, Scikit-Learn**
- Tools: **Notebook, Streamlit (for UI demo), Docker (for deployment)**
- Operating System: **Ubuntu 20.04 / Windows 11**

X. DESIGN DOCUMENT

- **Architecture Components:**
  Input (text + face video + physiological signal) → Modality-specific Encoders (BERT, ViT, BiLSTM) → Multimodal Attention-based Fusion Layer → Emotion Classifier + GPT-based Response Generator → Conversation Output.
- **Modules:**
  - Input Interface
  - Feature Extraction
  - Fusion Mechanism
  - Emotion Classification Module
  - Response Generation
  - User Interface

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- **Diagrams:**

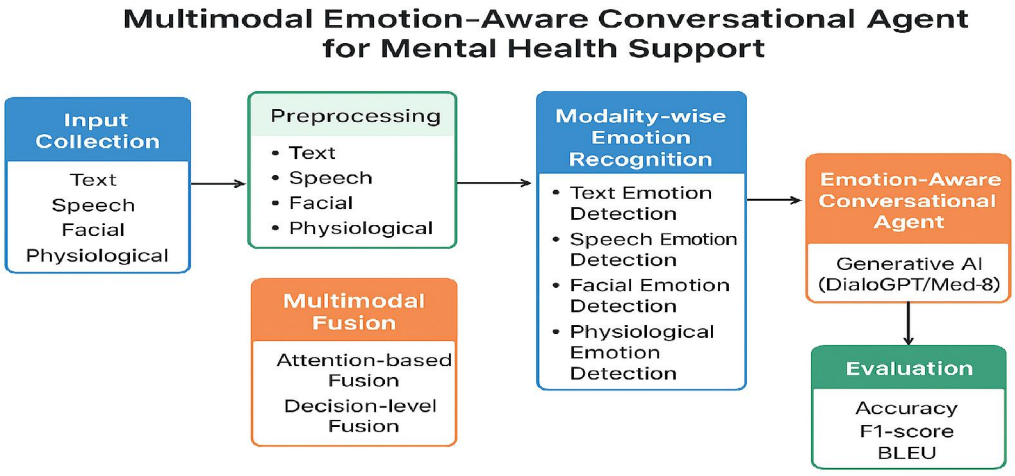

Fig No: 1 – System workflow

XI. ALGORITHM

Algorithm: Multimodal Emotion Recognition and Response

Input: User text, facial frames, physiological signal

Output: Emotion label + Empathetic response

Steps:

1. Extract text input, video feed, and biometric signal.
2. Preprocess text (tokenization), face (crop & normalize), and biometric data (resample/filter).
3. Generate embeddings:
   - BERT → E_T
   - ViT → E_F
   - BiLSTM → E_P
4. Fuse embeddings using attention-based weights.
5. Predict emotional state via classifier.
6. Generate response using GPT conditioned on emotion + context.
7. Display response with optional visuals.

XII. DATASETS

Dataset	Type	Size / Classes	Usage	Remarks
Go Emotions	Text-based Emotion Dataset	58,000 comments / 27 emotion labels	Model training	Covers diverse daily emotions in text form
Affect Net	Facial Emotion Dataset	~450,000 images / 8 basic emotions + neutral	Model training	Large-scale dataset for real-world facial emotion recognition

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K-EmoCon	Physiological Emotion Dataset	8.2 hours of bio signal recordings with emotion annotations	Multimodal fusion	Captures emotions using EEG, GSR, HR with video context
RAVDESS	Audio-Visual Emotion Dataset	1440 audio-visual clips of 8 emotions	Additional testing	Useful for cross-modal emotion and speech testing
Empathetic Dialogues	Conversational Text Dataset	25,000 dialogue examples	Response generation	Designed specifically for training empathetic responses

XIII. TEST SPECIFICATION

 Performance Metrics: Accuracy, Macro F1-score, Unweighted Average Recall (UAR), Response Empathy Score.

 Evaluation: Compare unimodal vs multimodal emotion detection and response generation

 Scenarios:

- Text-only vs multimodal (text + face + physiology)
- Real-time vs batch processing
- Neutral vs emotionally intense responses
- Clean input vs noisy input (e.g., low light, masked face, incomplete text)
- Single emotion vs mixed emotional states

Testing Parameters:

Parameter	Description / Purpose	Threshold/ Expected
Accuracy	% of correctly detected emotions	≥ 85%
Precision	True positive rate	≥ 80%
Recall	Sensitivity to all emotions	≥ 80%
F1-Score	Harmonic mean of precision & recall	≥ 82%
Latency	Time to generate response	≤ 2 seconds
User Satisfaction	Feedback from user surveys	≥ 4/5 rating

Test Cases:

Test Case ID	Scenario	Input	Expected Output
TC-01	Text Emotion Recognition	Text sentence input	Correct sentiment/emotion classification (Happy, Sad, Angry, Neutral)
TC-02	Facial Emotion Recognition	Image from webcam	Correct emotion detected (Happy, Sad, Surprise, Anger, Fear, Disgust, Neutral)
TC-03	Physiological Emotion Detection	Heart rate, GSR, EEG	Correct emotional state inferred

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TC-04	Multimodal Fusion	Combined inputs (Text + Face + Physiology)	Accurate final emotion prediction
TC-05	Generative AI Response	Detected emotion as input	Emotion-aware, empathetic response
TC-06	System Latency Test	Multiple concurrent inputs	Response generated within 1–2 seconds

XIV. CONCLUSION

This research introduces a multimodal emotion-aware conversational agent that improves mental health support by using text, facial cues, and physiological signals together. The system combines BERT for language understanding, Vision Transformers for facial emotion recognition, and BiLSTM models for physiological data, allowing it to capture emotional information that single-modality systems often miss. With a cross-attention fusion mechanism, these features are effectively integrated, resulting in more accurate emotion prediction across datasets like GoEmotions, AffectNet, and K-EmoCon. The inclusion of a generative response module further helps the agent deliver emotionally appropriate and supportive replies. Overall, the research demonstrates that multimodal deep learning can enhance the emotional intelligence and usefulness of conversational agents in mental health contexts.

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