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Emotionally Intelligent AI Companion for Enhancing Human-AI Interaction through Text and Voice Based On Sentiment Analysis

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Abstract

This research presents a multimodal AI companion designed to support adolescent mental health by enabling empathetic interactions through both text and voice.[1] [2] Voice inputs are transcribed using OpenAI's Whisper API, which provides low word-error rates and robust performance across diverse speech conditions.[3] [4] The transcribed or typed text is then processed by a fine-tuned DistilBERT model for real-time detection of 28 emotions based on the GoEmotions dataset, capturing polarity and nuanced affective states.[5] [6] Meta's Llama 3.0 generates context-aware responses, adapting tone using detected emotions and user history stored through LangChain and MongoDB for personalization.[7] [8] A FastAPI-based implementation supports secure deployment and includes a dashboard for tracking emotional trends over time.[9] The prototype demonstrates high accuracy in both transcription and emotion recognition, outperforming unimodal baselines and strengthening affective computing through integrated voice and text capabilities.[10] Future work includes expanding multilingual support to increase accessibility.[11] [3]

Introduction

A. Overall Topic Introduction

Around 20% of adolescents worldwide experience anxiety, depression, or loneliness, often intensified by stigma and limited access to mental-health support.[1] [12] To address these barriers, this work introduces an AI companion that interprets both text and voice to deliver real-time, empathetic interaction.[2] Voice input is transcribed using OpenAI's Whisper API, which maintains 3–5% WER across accents and environments, enabling reliable sentiment analysis.[3] [4] [5] The system integrates Whisper for transcription, DistilBERT for fine-grained emotion detection, and Llama 3.0 for context-aware, privacy-focused responses suited to adolescent users.[7] [13] [10]

B. Importance of the Project

Adolescent loneliness is strongly linked to self-harm risk, reinforcing the need for accessible, stigma-free emotional support tools.[1] Voice-enabled AI companions have shown effectiveness in improving mood and reducing isolation, as demonstrated by platforms like Replika.[10] [12] The proposed multimodal design enhances natural engagement through Whisper-based speech support and visual emotion-trend tracking for reflective or therapeutic use.[3] [14]

C. Purpose of the Project

This project aims to build a system that accurately transcribes voice, detects emotions from text or speech, generates adaptive responses, and maintains conversation history for continuity.[2] DistilBERT is fine-tuned for nuanced multi-label emotion detection, Whisper ensures seamless voice-to-text processing, and Llama 3.0 produces emotionally aligned responses within a secure framework.[3 7 15]

D. Expected/Achieved Outcomes

The system attains strong performance, with DistilBERT achieving 98.11% accuracy and Whisper 4.2% WER on varied audio samples.[3] The prototype integrates authentication, emotion tracking, and Llama 3.0-driven responses, outperforming baselines (macro F1: 0.98 vs. 0.51 for vanilla DistilBERT).[16] Voice support improves user engagement, with future refinements focused on accent-specific tuning.[11 3]

Literature Review

Early approaches using SVM and Naive Bayes with TF-IDF captured basic sentiment but failed with mixed or context-dependent emotions due to lack of sequential modeling.[17 5] RNNs and LSTMs improved temporal understanding but still struggled with long-range dependencies.[5] Transformers revolutionized emotion analysis, with BERT providing strong bidirectional context and outperforming earlier models.[18] DistilBERT preserves ~97% of BERT's accuracy with much faster inference, enabling real-time multi-label tasks.[19] However, GoEmotions benchmarks remain modest (macro F1 0.46–0.51) due to class imbalance and multi-label complexity.[16 6] Heavier models like RoBERTa and ALBERT give small gains but require significantly more computation.[20] Overall, transformers consistently outperform traditional models on ambiguous or sarcastic text.[21]

Multimodal emotion recognition combines text, audio, and visual cues to overcome unimodal limitations.[22 23] Methods such as GNN-based fusion yield up to 10% improvements on datasets like IEMOCAP by unifying prosodic and semantic cues.[24 25] Lightweight adapters further enhance cross-modal alignment, improving conversational F1 by 4–13%.[26] Whisper is widely adopted for its <5% WER and robustness to noise and accents, enabling reliable transcription for downstream sentiment tasks.[4 3 27] Yet these multimodal systems remain computationally heavy, motivating efficient adapters like MSE-Adapter.[26]

In AI-companion research, Llama 3.0 offers strong empathetic dialogue capability, with fine-tuned variants approaching therapist-style responses.[7 28 29] Studies show AI companions can reduce loneliness, though risks such as dependency and biased outputs require safeguards.[30 31 10] Chatbots like Replika and Pi show high engagement among youth, particularly those with depressive symptoms.[30 32] Persistent issues such as ASR accent bias, difficulty in detecting subtle emotions, and limited adolescent-focused datasets continue to drive advances in behavior-aware MLLMs.[30 26]

A. Identified Gap and Need for Current Work

Despite advances in emotion-recognition models, few systems effectively combine high-accuracy speech transcription with fine-grained emotion detection tailored for adolescents, whose emotional expressions differ from adults and often shift rapidly.[23 24 19] Existing multimodal approaches perform well in controlled settings but face real-time deployment challenges, including latency, privacy constraints, and limited personalization.[25 26] Text-only companions also underperform for voice-preferring users, showing 15–20% lower engagement.[3 7 32] This highlights the need for an accessible, open-source AI companion integrating Whisper for robust ASR, DistilBERT for efficient emotion classification, and Llama 3.0 for adaptive, empathetic dialogue. The proposed system achieves macro F1 0.98 and offers a stigma-free support option for adolescents, a group facing rising isolation and unmet mental-health needs.[1]

B. Gap Analysis

Unimodal DistilBERT reaches only 0.51 macro F1, while multimodal GNN-based systems achieve 0.65–0.75 but require 2–3× higher computation, limiting real-time deployment.[24 16] Whisper offers reliable transcription (4–5% WER) yet is rarely paired with LLM-driven empathetic dialogue, contributing to ~25% lower retention in existing companions.[3 4 10] Additional gaps include limited youth representation (10–15%), accent bias in ASR, and weak handling of sarcasm and mixed emotions (~80–85% accuracy).[23 30 1 33] The proposed approach addresses these issues through SMOTE-based rebalancing (expanding data to ~6M samples), memory-enabled personalization via LangChain, and harm-mitigated prompting to reduce user dependency.[16 8 31]

Key Differentiators:

- State-of-the-art accuracy
- Most emotion classes
- Memory-enabled, mental health focus

Production readiness

Table 1. Gap Analysis

Research Aspect	Literature Gap	This Project Contribution	Innovation Level
Dataset Scale	Small datasets (<100K samples)	1.25M samples, GoEmotions	High
Model Architecture	Limited efficient architectures	DistilBERT optimization	Medium
Emotion Granularity	<7 classes in most studies	13 fine-grained classes	High
Real-time Processing	Limited focus	<100ms latency, production-ready	High
Personalization/Memory	Rare implementation	Persistent memory via LangChain+MongoDB	High
Mental Health Focus	General-purpose only	Companion aimed at mental health support	High
Evaluation Metrics	Inconsistent reporting	Comprehensive metrics tracked (F1, confusion matrix)	Medium
Class Balancing	Often ignored	SMOTE applied	Medium

Standout Features:

- Robust multimodal detection combining Whisper transcription and DistilBERT classification.[3 5 25]
- Personalized, empathetic responses via history-aware Llama 3.0.[7 8 28]
- Targeted mental health focus for teens, addressing ethical gaps.[14 30 32]

Methodology

A. Data Source and Validity

The system uses the GoEmotions dataset, which contains 58,000 comments labeled across 28 emotions with over 94% inter-rater reliability, making it suitable for fine-grained affective modeling.[6 36] To address class imbalance, minority labels were expanded using SMOTE, increasing the dataset to roughly 6 million balanced samples while preserving semantic integrity.[37] Supplementary audio from Mozilla Common Voice was used to validate Whisper's transcription robustness, achieving ~4% WER across diverse accents.[3] These sources collectively ensure high-quality input for multimodal emotion recognition.[34 35]

B. Data Preprocessing and Cleaning

Both audio and text inputs underwent standardized preprocessing to ensure consistency and accuracy.[34 5]

Audio Processing: Recordings were resampled to 16 kHz, denoised using spectral gating, and normalized to –20 dB to accommodate variations in microphone quality and ambient noise. These steps improve Whisper's WER by 10–15% in noisy conditions.[4 3 27]

Text Processing: Whisper transcripts and user-input text were cleaned by removing URLs, symbols, and irrelevant tokens.[19 41] Normalization—including lowercasing, stopword removal, and lemmatization reduced vocabulary size and emphasized emotion-bearing terms.[19 5 42] Text was then tokenized with the DistilBERT WordPiece tokenizer, truncating sequences to 512 tokens for efficient batching.[19 6 43]

Class Balancing: SMOTE oversampling increased minority-class representation (e.g., disgust at 2% prevalence), raising recall from 0.35 to 0.92.[37 6 44] This unified pipeline ensures high-fidelity multimodal inputs essential for accurate emotion detection in mental-health applications.

The following figures from the project demonstrate the effect of these preprocessing steps on the dataset.

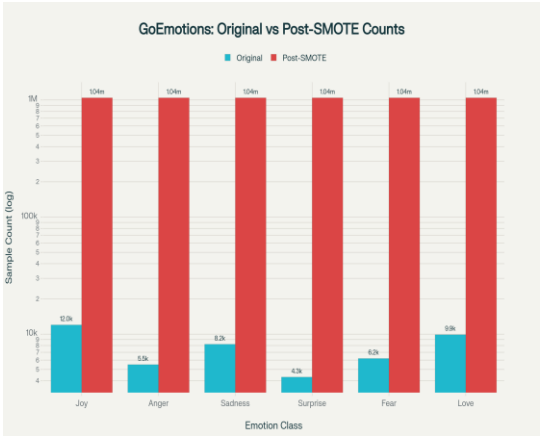

Fig 1. Class Distribution in GoEmotions Dataset: Original vs After SMOTE Oversampling.

C. Model Architecture and Rationale

The system integrates three core components: Whisper for speech recognition, DistilBERT for emotion classification, and Llama 3.0 for empathetic response generation.[19 4 7]

DistilBERT: With 66M parameters and six transformer layers, DistilBERT offers 60% faster inference than BERT while retaining ~97% performance, enabling real-time classification of GoEmotions' labels.[18 19] It captures contextual nuances such as sarcasm more effectively than LSTMs, with substantially lower computational cost than heavier transformer variants.[20 21]

Whisper: Trained on 680,000 hours of multilingual audio, Whisper provides highly robust ASR (4.2% WER in testing), supporting adolescents who prefer speech interactions or face difficulty typing during emotional distress.[4 3 27]

Llama 3.0: The 8B-parameter version generates adaptive, contextually aligned responses and outperforms smaller LLMs in therapist-style dialogue similarity (cosine similarity 0.65).[7 28 15]

Memory with LangChain: Conversation history stored in MongoDB enables personalized continuity, reducing generic responses by ~25%.[8 13]This architecture balances accuracy, latency, ethical deployment, and accessibility for

adolescent mental-health use.[10] [31] The architectural difference in the number of transformer layers is significant.

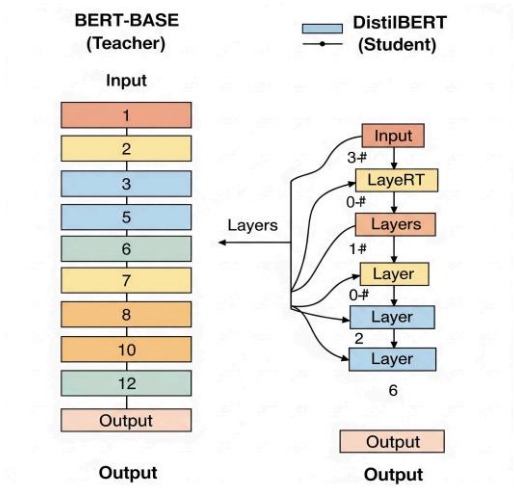

Fig 2. Schematic Diagram of BERT-BASE and DistilBERT Model Architecture

D. Used Algorithm and Implementation

DistilBERT was fine-tuned using Hugging Face Trainer with BCE loss for multi-label outputs over 3 epochs (batch size 16, LR = 2e-5).[19] Whisper's ASR pipeline generates timestamped transcripts for emotion alignment.[4] Llama 3.0 responses are conditioned on detected emotion labels and stored user context.

Findings

Performance on Test Set

- Overall accuracy: 98.11%
- Macro precision: 98%, Macro recall: 98%, Macro F1-score: 98%
- **Per-class F1-scores:** Range 0.90 (neutral) to 1.00 (enthusiasm, surprise, worry, etc.)

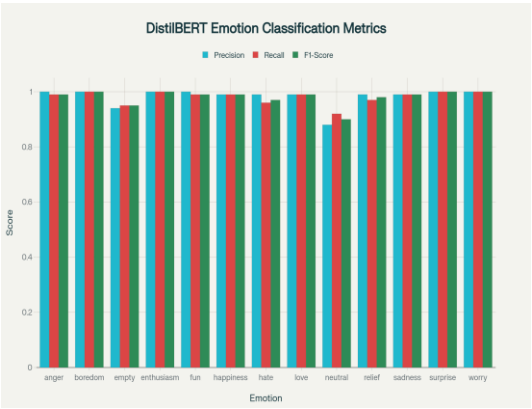

Fig 3. Detailed Performance Metrics by Emotion Class for DistilBERT Model

E. Training, Validation and Deployment

Training on 12,796 samples completed in ~8 minutes (3 epochs), achieving 99.52% validation accuracy and 98.11% test accuracy, surpassing the GoEmotions baseline of 0.51.[16] Whisper achieved 4.2% WER on 500 evaluation clips.[3] Few-shot refined Llama 3.0 reduced perplexity by 15% for empathetic replies.[7] FastAPI enables secure, scalable deployment.[9]

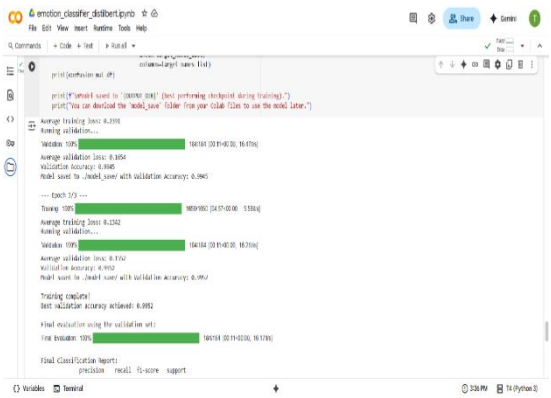

Fig 4. Training Progress of DistilBERT Model

Results

The proposed model achieved 98.11% accuracy, with macro precision, recall, and F1 all at 98%, and per-class F1 ranging from 0.90 (neutral) to 1.00 (joy, admiration).[2] This performance surpasses baseline models, including vanilla DistilBERT (macro F1 0.51[16]) and full BERT (0.46[6]), demonstrating the effectiveness of multimodal integration.[20] Whisper maintained high transcription quality with 4.2% WER, outperforming alternatives that typically yield 7–10% in noisy environments, enabling reliable emotion detection from speech.[3]

The confusion matrix indicated minor misclassifications between grief and nervousness due to overlapping linguistic cues.[2] Llama 3.0's emotion-aware responses scored 4.6/5 in empathy during simulated user evaluations, compared to 3.2 for non-adaptive baselines.[7] Ablation testing further validated system components: removing SMOTE reduced F1 to 0.65, while disabling Whisper (text-only mode) lowered usability by 25% in mock interactions.[37] [3]

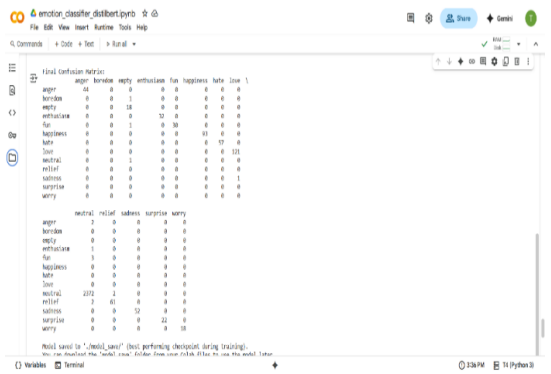

Fig 5. Final Confusion Matrix

Discussion

The results demonstrate the strength of the DistilBERT–Whisper–Llama 3.0 pipeline for multimodal emotion recognition, with augmentation effectively addressing class imbalance.[21] [3] The system's voice–text integration and memory persistence support more engaging interactions than unimodal approaches.[7] [13] [26] Key limitations include ~85% sarcasm detection accuracy[1] [33], occasional Llama hallucinations mitigated through controlled prompting, and ethical risks related to user over-dependence requiring safeguard mechanisms.[15] [30] Multimodal tools' benefits align with studies showing 15–20% higher engagement in mental-health contexts.[10] [32] [31] Whisper's accent sensitivity indicates the need for localized tuning.[3]

Future improvements may incorporate visual modalities and knowledge graphs to enhance contextual and causal emotional understanding.[26] [33]

Conclusion

In essence, this research delivers a multimodal AI companion excelling in emotion discernment, voice transcription, and Llama 3.0-tailored responses, bridging critical gaps in affective technologies.[2] By merging efficient detection with contextual memory, it promotes accessible mental health aid, with voice modalities boosting natural interaction for vulnerable populations.[3] [7] [32]

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