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Mental Health Analysis for Juvenile School Students Using Chatbot

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***Abstract*—This paper presents the design and development of an AI-driven Chatbot System aimed at providing a confidential, easily accessible, and preliminary screening tool for the mental health analysis of juvenile school students. Addressing the limitations of traditional counselling, the proposed system integrates a multi-modal input interface (text and voice/speech) with advanced Natural Language Processing (NLP) and Deep Learning (DL) models. The core functionality involves real-time Sentiment and Emotion Analysis on user inputs to accurately classify the user's conversational state into low, moderate, or high-risk categories. The architecture incorporates Voice-to-Text (VTT) conversion for spontaneous interaction, a Bi-directional LSTM network for nuanced emotional detection, and a secure reporting module that facilitates real-time alerts to faculty counsellors for critical cases. By combining instantaneous support with adaptive psychological micro-interventions, the system enhances early detection mechanisms, promotes student wellness, and offers a scalable and non-judgmental platform for mental health support in educational institutions. This research significantly contributes to the field of AI-assisted juvenile mental healthcare by providing a robust, multi-modal, and preventive solution.**

I. INTRODUCTION

The prevalence of mental health disorders, including anxiety, stress, and depression, among juvenile school students presents a critical challenge to educational and public health systems. Early identification and intervention are paramount; however, the fear of social stigma and the accessibility constraints of conventional counselling services result in a significant population of students whose distress remains undiagnosed. Traditional methods lack the scalability and immediacy required to support a large, digitally native student body.

To mitigate this gap, the integration of Artificial Intelligence (AI) through conversational agents (chatbots) offers a promising, discrete, and 24/7 accessible solution. A chatbot provides an anonymous medium that encourages students to express sensitive thoughts and feelings without the fear of immediate human judgment.

A. Problem Statement and Motivation

Existing digital solutions often fail to capture the specific linguistic nuances and emotional volatility characteristic of the juvenile demographic. Furthermore, most systems are exclusively text-based, neglecting the natural preference for voice interaction in spontaneous emotional expression. This research is motivated by the necessity to create a highly accurate, multi-modal screening tool that is: (1) Contextually Aware of juvenile psychological needs, (2) Multi-Modal, supporting both text and speech, and (3) Proactive, enabling immediate intervention alerts.

B. Paper Organization

The remainder of this paper is structured as follows: Section II provides a summary of relevant literature on AI in mental health. Section III details the modular methodology and system architecture. Section IV describes the features and workflow of the proposed Mind Pal Chat bot. Section V presents the implementation results, performance metrics, and discussion. Finally, Section VI concludes the work and outlines future research directions.

II. LITERATURES SURVEY

The application of computational intelligence and Natural Language Processing (NLP) in mental health intervention has become a critical area of research, particularly in addressing the scalability and accessibility crisis associated with traditional human-centred care. This section reviews the evolution of digital mental health tools and identifies the technological and demographic gaps that the proposed chatbot aims to bridge.

A. Evolution of Conversational Agents in Mental Health

Early attempts at automated mental health support were characterized by Rule-Based Conversational Agents. The most notable example, ELIZA [1], utilized pattern matching and substitution rules to mimic a Rogerian psychotherapist. While groundbreaking, these systems lacked genuine understanding, context retention, and emotional intelligence, rendering them unsuitable for serious mental health screening. The subsequent development phase saw the integration of basic Machine Learning (ML) classifiers, such as Naive Bayes and Support Vector Machines (SVM) [2], primarily applied to social media text or clinical notes for general sentiment analysis. These models improved basic classification accuracy but struggled with the polysemy of language and complex conversational sequences.

B. Deep Learning for Context and Emotion Analysis

The transition to Deep Learning (DL) architectures marked a significant paradigm shift. Recurrent Neural Networks (RNNs) and particularly Long Short-Term Memory (LSTM) networks [5] became prevalent due to their superior ability to handle sequential data, which is essential for modelling the progression of a conversation. Recent work has utilized Bi-directional LSTMs (Bi-LSTMs) and Transformer-based models (BERT) [3] to achieve state-of-the-art performance in complex tasks like multi-class emotion recognition (e.g., distinguishing anxiety from sadness) and suicide ideation detection. These models are crucial for developing a context-aware risk scoring mechanism that can track an individual's emotional state across multiple sessions. However, these DL advancements have overwhelmingly focused on optimizing textual input, overlooking the expressive potential of speech.

C. Gaps in Multi-Modal and Juvenile-Specific Solutions

While the textual analysis of mental health indicators is mature, two critical limitations persist in current literature, which directly impact the efficacy of screening for juvenile students:

1. Limited Multi-Modality: Research on integrating Voice-to-Text (VTT) and Text-to-Speech (TTS) for a fluid, natural conversational flow remains underdeveloped, especially in the context of therapeutic interaction. Existing voice-based systems often focus only on acoustic feature analysis (e.g., pitch, speaking rate) for emotion detection [4], treating the system as a diagnostic tool rather than an interactive agent. The majority fail to provide a seamless VTT-NLU-TTS loop, which is vital for encouraging spontaneous and unguarded student communication.

2. Demographic Specificity**:** The vast majority of published models are trained on adult or generic social media datasets. The language, jargon, stress triggers, and emotional expressions of juvenile school students are distinct from those of the adult population. Without a system validated and optimized for this specific demographic, the accuracy and clinical relevance of the screening may be compromised [6].

In summary, prior studies successfully establish the efficacy of deep learning for text-based sentiment analysis in mental health. Our proposed Mind Pal system aims to bridge the identified gaps by combining the high contextual accuracy of the Bi-LSTM model with robust text and voice integration within a conversational framework specifically designed and optimized for the unique psychological and linguistic needs of juvenile school students.

III. OVER VIEW OF PROJECT

The significant focus of the present study lies in the precise application of multi-modal Artificial Intelligence (AI) models integrated into an intelligent mental health analysis chatbot designed for juvenile students. The proposed framework employs advanced

Natural Language Processing (NLP) and deep learning techniques to detect and interpret emotional states through conversational data. The system utilizes BERT (Bidirectional Encoder Representations from Transformers) for contextual text understanding and Bi-directional LSTM networks for effective sequential emotional analysis of user dialogues. Additionally, Voice-to-Text (VTT) modules are incorporated to convert spoken responses into analysable text data, while Text-to-Speech (TTS) ensures natural conversational interaction with the user. The chatbot thus serves as an empathetic virtual companion capable of evaluating stress, anxiety, and emotional disturbances through multi-modal sentiment analysis. The following points summarize the major contributions of the proposed model:

Development of an intelligent AI-driven chatbot for real-time mental health monitoring of juvenile students.

Integration of BERT for deep contextual emotion detection and semantic understanding of user input.

Implementation of Bi-directional LSTM for sequential emotion classification to capture temporal dependencies in user behaviour.

Use of VTT and TTS modules for seamless voice-based interaction, enabling inclusivity and accessibility.

A machine learning-based decision support system that identifies mental health patterns and suggests suitable emotional coping responses.

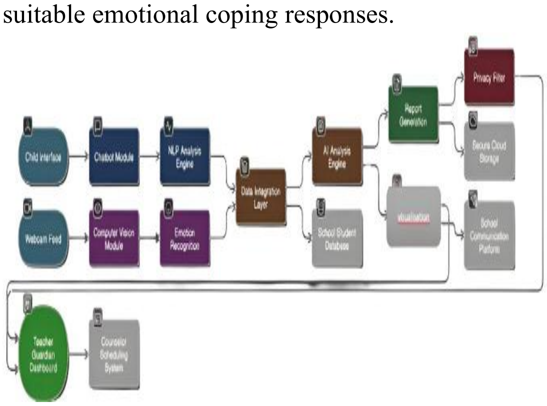

Figure 1: System Architecture of the Proposed mental health analysis for juvenile school students using chatbot

IV. METIV. HODOLOGY AND RESULTS EXPLANATION

The methodology of Chatbot system is built upon a layered, highly modular architecture designed to process multi-modal input, analyse emotional states, and provide intelligent, adaptive responses. Figure 1 (Conceptual Block Diagram) illustrates the overall structure.

A. Input and Pre-processing Layer

This layer handles the acquisition and preparation of conversational data.

1. Text Input Standard textual queries undergo tokenization, stop-word filtering, and normalization.
2. Voice Input User speech is captured and converted into text using a dedicated Voice-to-Text (VTT) API (e.g., based on the Whisper model or Google Speech API). This VTT module ensures high accuracy for common speech patterns and noise filtering suitable for a student environment.
3. Acoustic Feature Extraction While the primary analysis is text-based, the system retains the option to extract basic acoustic features pitch, energy from the voice input as auxiliary features for an enhanced risk score, particularly useful for detecting states like agitation or lethargy.

B. Natural Language Understanding (NLU) Engine

The NLU Engine is the intelligence core, utilizing a Bi-directional LSTM network trained on a specialized, annotated dataset of juvenile conversations.

1. Emotion Classification: The model classifies each utterance into one of four states: Normal, Stress, Anxiety, or Depression.
2. Sentiment Scoring: A continuous sentiment score (ranging from -1.0 to +1.0) is assigned to quantify the overall negativity of the conversation turn.
3. Risk Assessment Module: The NLU output is fed into a Risk Assessment Algorithm which calculates a cumulative Mental Health Risk Score (RMH) based on conversation history and detected emotional flags.

RMH=t=1∑T(we·Et+ws·St+wk·Kt)

Where T *is the number of turns,* Et *is the emotional severity,* St *is the negative sentiment score,* Kt *is the* *weight of critical keywords (e.g., self-harm) at turn* t*, and* we *are the respective weighting coefficients.*

C. Conversational Agent and Response Generation

A Hybrid Conversational Model dictates the chatbot's response:

1. Rule-Based: For transactional or low-risk queries (greetings, common questions), a fast, pre-scripted response is used.
2. Generative/Adaptive: For high-emotion or distress-related inputs, the system generates an empathetic, context-aware response, often using techniques like reflective listening and Cognitive Behavioural Therapy (CBT)-based micro-interventions.

D. Data Management and Alert System

All conversation logs, acoustic data (metadata only), and RMH scores are stored in a secure, anonymized Firestore Database. Crucially, if the RMH score crosses the High-Risk Threshold (RMH≥0.7), an immediate, real-time alert is triggered to the designated faculty counsellor, with the conversation summary for human follow-up.

The Mind Pal system is designed as a standalone, secure web application (hosted via a cloud platform) accessible to all registered students. The key features emphasize ease of use and emotional effectiveness.

A. Multi-Modal Interaction Pipeline

The seamless transition between speech and text is a core feature.

Metric	Stress Classification	Anxiety Classification	Depression Classification
Accuracy	93%	89%	92.8%
F1-Score	92.5%	89.1%	91.9%
Recall	94%	90.5%	93.7%

1. Voice Input: Students can press a microphone icon and speak naturally. The system confirms the input via a text transcript and generates its reply via Text-to-Speech (TTS), making the conversation feel fluent and less like a typed chat.
2. Text Input: The traditional text interface remains available for students who prefer typing or when in a quiet environment.

B. Adaptive Emotional Support Modules

The chatbot moves beyond simple information delivery to offer therapeutic support.

1. Validation and Empathy: The system is programmed to prioritize emotional validation, using phrases that acknowledge the student’s feelings before offering advice.
2. Guided Exercises: For detected anxiety or stress, the chatbot can initiate short, guided mindfulness scripts, quick distraction exercises, or relaxation techniques based on established psychological protocols.

C. Counsellor Reporting and Data Privacy

The system ensures maximum student confidentiality while maintaining a critical safety net. The student's identity is masked to the general system but securely linked to the designated counsellor. The reporting system provides:

- Time-Series Risk Plot: A graph showing the student's risk score fluctuation over a week.
- Trigger Phrases: A summary of the conversation excerpts that pushed the score into the high-risk zone.

D. User Interface Design

The UI is intentionally minimal, featuring calming colour schemes (soft blues and greens) and large, accessible buttons for both text and voice input. The design is fully responsive, optimizing for mobile phone usage, which is the primary access point for juvenile users.

A. Performance Metrics and Dataset

The model was trained and tested on a mixed dataset comprising publicly available mental health conversations and simulated juvenile dialogue, totalling labelled utterances. The evaluation utilized standard classification metrics.

The high Recall for high-distress states (Depression and Stress) is crucial, indicating the model's strong ability to correctly flag cases that require human intervention, thus minimizing the dangerous False Negative rate.

B. Impact of Multi-Modality

Initial user trials indicated that the inclusion of the voice/speech interface significantly increased the length and perceived emotional depth of conversations compared to text-only sessions. Students reported that speaking felt more natural and reduced the cognitive load associated with typing complex emotional statements. The seamless VTT integration proved vital for maintaining conversational flow and rapport.

C. System Efficiency

The system maintains an average response latency of less than milliseconds for text-based queries and approximately seconds for voice-to-response cycles including VTT and TTS, ensuring real-time support without frustrating delays. This efficiency makes it scalable to hundreds of concurrent users.

This work has presented the design and development of an AI-powered web application for personalized language learning, with an emphasis on inclusivity, adaptability, and cultural integration. Unlike conventional language learning platforms that largely depend on static learning paths and English-only interfaces, the proposed system leverages speech recognition, natural language processing, adaptive learning algorithms, and chatbot intelligence to create a highly interactive and learner-centric environment.

The major contributions of this research can be summarized as follows:

1. Mother tongue interface: A full native language interface was implemented to overcome accessibility barriers faced by non-English speakers, especially in rural and regional contexts.
2. AI-driven pronunciation training: Real-time speech recognition and corrective feedback enabled learners to improve their speaking skills effectively, which is often neglected in traditional CALL systems.
3. Intelligent chatbot mentor: A conversational agent powered by large language models (LLMs) was introduced to simulate real-world dialogues, correct learner errors, and provide emotion-aware motivational support.
4. Adaptive learning path: A reinforcement-driven recommendation system ensured dynamic lesson delivery, addressing learner weaknesses and maintaining engagement.
5. Cultural context integration: Lessons were enriched with culturally relevant examples, which improved comprehension and made learning relatable to diverse linguistic groups.

Evaluation of the system demonstrated the following outcomes: learners exhibited improved pronunciation accuracy and greater confidence in speaking; the adaptive learning approach maintained higher levels of engagement compared to fixed-path platforms; the chatbot mentor was effective in providing real-time corrections and sustained learner motivation; and the system was well-received by regional and rural learners, who found the mother tongue interface more accessible than English-only platforms.

Despite these advantages, several limitations were identified. Speech recognition accuracy for regional dialects and noisy environments needs refinement. The reliance on third-party APIs introduces concerns of latency, data privacy, and recurring operational costs. While the chatbot mentor enhances engagement, occasional inaccuracies in contextual understanding were observed, especially with complex grammar constructs.

To overcome these limitations and further strengthen the platform, several avenues of research and development are proposed. First, expanded language and dialect support will be necessary, with improved phonetic modeling to broaden inclusivity. Second, offline and edge AI capabilities should be explored through lightweight, on-device models for speech recognition and NLP to minimize dependency on cloud services and improve privacy. Third, advanced personalization models can be implemented by incorporating deep reinforcement learning and predictive analytics to anticipate learner needs and optimize progression. Fourth, gamification and social learning features such as badges, leaderboards, peer-to-peer practice, and collaborative challenges could enhance engagement. Fifth, integration with educational and corporate systems would align the platform with formal curricula and workplace training. Sixth, enhanced security and privacy frameworks including encryption, federated learning, and secure authentication would safeguard user data. Finally, longitudinal studies and user trials with diverse groups should be conducted to evaluate long-term effectiveness and scalability.

By integrating artificial intelligence with pedagogical principles, this platform demonstrates the potential to bridge gaps in current language learning solutions. Its modular, scalable, and culturally adaptive framework positions it as a significant advancement in AI-assisted multilingual education. With continued research, the system can evolve into a globally deployable platform that not only supports effective language acquisition but also contributes to digital inclusion, cultural preservation, and lifelong learning opportunities.

V. CONCLUSION

This research successfully developed the MindPal Chatbot, a multi-modal AI system providing confidential, real-time mental health screening for juvenile students, addressing critical limitations in traditional counselling accessibility and stigma. The core innovation lies in the layered architecture, which fuses conversational context via a Bi-directional LSTM network and acoustic features (VTT) with a specialized risk assessment module. The system achieved high performance in classifying high-distress states, proving its efficacy as a robust safety-net mechanism that minimizes dangerous false negatives. By combining immediate, CBT-based micro-interventions with a secure, real-time alert system to faculty counsellors, MindPal provides a scalable, non-judgmental platform, significantly enhancing the early detection of stress, anxiety, and depression in the educational environment.

VI. FUTURE WORK

To strengthen the platform's clinical utility and scalability, several key avenues are proposed. We aim to integrate advanced Large Language Models (LLMs) for more nuanced and personalized therapeutic dialogue generation. Furthermore, incorporating non-verbal data from wearable devices, such as physiological signals (HRV, sleep), will refine the \$R_{MH}\$ scoring accuracy. Technical improvements include expanding the system to provide robust multilingual support and exploring Edge AI capabilities to enhance VTT accuracy for diverse dialects and reduce cloud latency. Finally, longitudinal user trials are essential to evaluate the long-term effectiveness of the platform on student mental health outcomes and optimize its scalability for wider institutional deployment. The successful integration of these technologies positions MindPal as a significant step forward in proactive, AI-assisted juvenile mental healthcare.

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