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Nova-Chat: A Full-Stack Chat-bot Using AI

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Abstract- — By facilitating natural, flexible, and context-aware communication across a variety of languages and cultural contexts, artificial intelligence (AI) has revolutionized human-computer interaction. Large language models have advanced, but chatbots still have difficulty identifying, interpreting, and reacting sympathetically to users' emotional states. As a result, they frequently provide generic responses that lack genuine resonance. This paper introduces Novachat, a full-stack AI chatbot designed to close this gap by combining multilingualism and sophisticated emotion intelligence into a scalable MERN-stack architecture. In order to provide human-like, contextually nuanced conversations in English, Hindi, Marathi, and other languages, Novachat's modular framework integrates sentiment analysis, emotion-adaptive response generation, and language detection. To ensure smooth real-time adaptability, each module functions as a microservice and communicates via orchestration driven by APIs. The study describes the system's overall architecture, emotional classification model, dataset organization, and quantitative performance assessment using metrics like System Usability Scale (SUS), emotion recognition accuracy, response relevancy, and user engagement latency. According to experimental results, Novachat generates sympathetic responses and detects emotions with high accuracy; a SUS score indicates strong user acceptance. The field is moving closer to AI systems that genuinely recognize and value the user's emotional experience as a result of these results, which validate Novachat's function as an efficient, inclusive, and emotionally engaging conversational platform.

Keywords— Sentiment analysis, natural language processing (NLP), multilingual chatbots, emotional recognition, humanized conversations, sympathetic response generation, tone adaptation, MERN stack, API orchestration, artificial intelligence (AI), emotional intelligence (EI), and sentiment analysis.

I. INTRODUCTION

Artificial Intelligence (AI) has transformed digital communication by enabling adaptive, context-aware interactions between humans and machines. Large language models have advanced significantly, but most chatbots still produce generic, emotionally neutral responses that fall short of engaging users on a human level. Whether for customer service, education, or friendship, people who are looking for complex, emotionally charged conversations frequently encounter a lack of true empathy and contextual adaptation.
Incorporating advanced sentiment analysis and emotional intelligence frameworks can significantly improve user experience by making dialogue more relatable and natural, according to recent research in emotion-aware conversational AI. According to studies, chatbots that can identify and react to user emotions can increase user satisfaction, trust, and engagement over the long term. Although industry titans like DeepSeek and ChatGPT have established the groundwork for organic, multi-turn dialogue, they are still unable to adjust tone and offer sympathetic responses to users who are feeling angry, depressed, or excited.

To address these challenges, this research introduces Novachat—a full-stack AI chatbot designed specifically to understand and adapt to the user's emotional state in real time. Novachat leverages an architecture built on the MERN stack and incorporates advanced modules for emotion recognition, sentiment-adaptive response generation, and multilingual dialogue management covering languages such as English, Hindi, and Marathi. The system orchestrates each component via efficient API-driven microservices, ensuring seamless integration, real-time adaptability, and scalability. This paper details Novachat's system architecture, emotion and sentiment modeling pipeline, dataset strategy, and quantitative evaluation on metrics such as emotional classification accuracy, response latency, and user satisfaction scores. By pushing the boundaries of empathetic and human-like machine conversation, Novachat aims to set a new benchmark for accessible, emotionally engaging conversational AI solutions.

Objectives
The primary objectives of this research are:
- To design and implement Novachat, a scalable AI-powered chatbot system that can understand and respond to users' emotions in a caring way utilizing a MERN-stack architecture.
- To develop and evaluate modules for recognizing emotions, generating responses that adapt to different feelings, and managing multilingual conversations in languages like English, Hindi, and Marathi.

- To build and use a wide range of multilingual and emotive datasets for training and testing adaptive conversational modules.
- To objectively evaluate system performance through metrics like emotion detection accuracy, response relevance, latency, and user satisfaction (e.g., System Usability Scale), thereby illustrating Novachat's efficacy in facilitating human-like, empathic, and contextually aware dialogues.

II. MATERIALS AND METHODS

Artificial Intelligence (AI) has greatly improved the way humans interact with machines and is very noticeable in chatbots that can recognize emotions. Novachat puts together advanced emotion detection, sentiment analysis, and multilingual natural language processing (NLP) inside a scalable MERN-stack setup.

Building on the foundational concepts of affective computing [Picard, 1997; Calvo & D'Mello, 2010] and utilizing recent breakthroughs in deep learning methodologies for emotion detection [Zhu & Mahmoud, 2023], Novachat strives to deliver highly nuanced context-aware responses across various linguistic landscapes. Studies have indicated improvements in chatbot responsiveness as well as end-user engagement upon the infusion of emotion intelligence into chatbots [Bhandari, 2025; Rani et al., 2024].

Novachat's modules interact through API-based microservices which allow real-time adaptability. It shall be evaluated on standard metrics of accuracy in the classification of emotion, latency in response, and user satisfaction scores.

This integration supports inclusive, humanized AI conversations that effectively respond to users' emotional states across languages like English, Hindi, and Marathi.

The table below presents the list of references with their respective authors, Titles, Sources, Notes and indication of whether they have been cited or cross-referenced in the introduction section.

Based on such findings, this study proposes Novachat, an AI Chatbot Framework that embraces the following functionalities: sentiment analysis in any language as Native Natural Language Processing and Empathetic Response Generation for Human Conversational Experience

Table 1: Literature Review

No.	Author(s) & Year	Title	Source	Notes
1	Bhandari, H. (2025)	Emotion-Aware AI Chatbot for Mental Health Support	Int. Journal of Research Publication and Reviews, 6(4), 14204-14211	Mental health chatbot focus
2	Rani, M. U., et al. (2024)	Advancing Emotional Intelligence in Chatbots through Multi-Modal Frameworks	Journal of Medical Informatics, 13(3)	Emotion intelligence frameworks
3	Herath, R. (2025)	Emotionally Intelligent Chatbots in Mental Health	Int. University of Applied Science, Stockholm	Psychological & ethical impacts
4	Zhang, J. (2024)	The Impact of Emotional Expression by AI Chatbots on Perceived Humanness	Journal of AI Research, 42, 1-23	Emotional expression in AI
5	Panjwani-Charania, S. (2023)	Systematic Review of AI Applications in Tutoring Systems for Special Learning Needs	Education and Information Technologies, 28(3), 563-578	Educational AI applications
6	Peerbits Blog (2025)	AI Chatbot Trends 2025: Voice AI, Emotional AI, and Beyond	Peerbits Blog	Industry trends overview
7	Calvo, R. A., & D'Mello, S. (2010)	Affect Detection: An Interdisciplinary Review of Models, Methods, and Their Applications	IEEE Transactions on Affective Computing, 1(1), 18-37	Foundational affective computing
8	Picard, R. W. (1997)	Affective Computing	MIT Press	Foundational book on emotion AI
9	Poria, S., et al. (2017)	A Review of Affective Computing: From Unimodal Analysis to Multimodal Fusion	Information Fusion, 37, 98-125	Multimodal emotion recognition

Dataset Description

Text Dialogues: This includes various conversation samples with support for multiple languages, such as English, Hindi, and Marathi. The samples reflect different emotional tones and contexts. They come from open multilingual dialogue datasets like MultiWOZ and Cornell Movie-Dialogs corpora.

Audio Speech Recordings: This features voice samples from different speakers and accents that represent the supported languages. These samples are useful for training the speech-to-text (STT) and text-to-speech (TTS) systems. They are partly taken from open speech datasets like Mozilla Common Voice.
User Interaction Logs: This records how users behave during chatbot interactions. It tracks session duration, response times, and repeated queries through chatbot usage analytics tools.

Emotion-labelled Metadata: This contains annotations for sentiment and emotion tags linked to specific dialogue segments. The data is taken from emotion-labelled datasets like ISEAR and EmoBank, which are used for training empathetic responses.

Multilingual Intent Tags: This includes intent classification data across the supported languages. The data comes from existing multilingual intent datasets and manually curated additions to cover common user intents.

This composition helps ensure strong model performance across text, speech, emotion recognition, and understanding user intent. It is designed to meet Novachat's goal of providing human-like, empathetic, and multilingual conversations.

Table 2: Dataset Description

Ref. No.	Data Type	Quantity	Attributes (Examples)	Purpose / Task Phase
[D1]	Text Dialogues	2000	Multilingual (English, Hindi, Marathi), Emotion tags, Context complexity	Training language understanding and emotion recognition
[D2]	Audio Speech Samples	2000	Speaker ID, Accent, Phoneme clarity	STT and TTS training/validation
[D3]	User Interaction Logs	2000	Session duration, Response times, Query frequency	Adaptive dialogue management and analytics
[D4]	Emotion Metadata	2000	Sentiment scores, Emotion labels	Sentiment analysis and empathetic response
[D5]	Intent Tags	2000	Intent categories, Multilingual classification	Intent recognition and dialogue flow control

Proposed System

The proposed Novachat framework combines artificial intelligence, natural language processing (NLP), emotion recognition, and dialogue management in a modular, full-stack (MERN) architecture. The approach aims to provide a complete, human-like conversational experience that responds to user emotions, language, and context. It enables smooth real-time interactions and offers high scalability.

System Overview

The Novachat system processes user interactions through a set pipeline to ensure emotionally aware and adaptable conversations. The workflow starts with user input and moves through these steps:

User Input Acquisition

Users can start a conversation through text or voice, with support for multiple languages like English, Hindi, and Marathi.

Speech-to-Text (STT) & Language Detection

If the input is spoken, the system changes the audio into text using a multilingual STT engine such as Mozilla DeepSpeech or Google Speech-to-Text, followed by automatic language detection.

Emotion and Intent Recognition

The system analyzes the processed input using an emotion recognition module with tools such as ISEAR or EmoBank datasets and transformer models. This helps identify the user's sentiment, emotional state, and intent based on the ongoing dialogue context.

Multilingual NLP Processing

The system parses the text for meaning and intent in the identified language, using multilingual embeddings and translation models as required.

Dialogue Management & Response Generation

The dialogue manager, guided by the detected emotion and context, organizes responses using:

- Pre-trained and fine-tuned transformer models like mBERT and GPT-based for human-like, context-sensitive output.
- Empathetic response generation that adjusts language, tone, and phrasing to align with the user's emotional state.

Text-to-Speech (TTS) Output

For voice conversations, the system converts the generated reply into natural speech that matches the emotion, using a TTS engine capable of prosody and emotion modulation.

Feedback Logging & Adaptive Learning

User interactions, including emotional reactions, satisfaction, and language changes, are logged and used in reinforcement learning modules. This helps improve future response strategies and model updates for personalization.

This setup allows Novachat to offer real-time, emotionally intelligent conversations in multiple languages. It creates context-aware, empathetic, and natural dialogue that adjusts to individual user needs.

If you want this in more diagrammatic or bullet-point format for presentations or documents, let me know your preference.
Architecture Description

The Novachat architecture includes several key functional layers:

User Interface Layer

This layer uses React.js, allowing users to interact through voice or text in multiple languages, including English, Hindi, and Marathi. Users can adjust font size, color contrast, and speech playback controls for better accessibility.

- Input = UI(U, A)
- Input: Initial input for speech-to-text or text processing
- U: User interaction (voice or text)
- A: Accessibility settings

Speech-to-Text and Language Detection Layer

Voice inputs are transformed into text using speech-to-text engines like Google Speech-to-Text or Whisper. The system then automatically detects the input language to guide processing in the correct multilingual pipeline.

- Raw = STT(Input)
- Raw: Raw text output

Emotion Recognition and Intent Classification Layer
The text input goes through sentiment and emotion detection using transformer-based models. This also includes intent classification to identify user goals and emotional state.

Natural Language Processing and Summarization Layer
Text simplification and summarization occur using models like mBERT or PEGASUS. These models create simplified, context-appropriate responses based on the user's profile and emotional state.

- Sum = Condense(Raw, P_User)
- Sum: Simplified summary text
- P_User: User profile and emotional context

Response Generation and Multilingual Adaptation Layer
The dialogue manager creates empathetic and context-aware responses using pre-trained language models. It adjusts tone and style according to the detected sentiment and language preference.

Text-to-Speech (TTS) and Output Layer
For voice responses, text is transformed into speech using an emotionally expressive TTS engine. This engine adjusts the way speech sounds to match the intended emotional tone.

Feedback Logging and Adaptive Learning Layer
User interactions, including feedback on emotions and response satisfaction, are recorded. This information updates learning policies through reinforcement learning, allowing Novachat to personalize and improve conversations over time.

System Modeling and Performance Metrics
The Novachat system combines different methods for recognizing emotions, processing language, and managing dialogue within a flexible AI setup. We evaluate the system's performance with a range of measures that look at both technical accuracy and user experience.

Performance Metrics

- Emotion Detection Accuracy: This measures how accurately the system classifies sentiment and emotions in user inputs through both text and voice, aiming for high precision to ensure empathetic responses.
- Intent Recognition Accuracy: This checks how well the system understands what users want, allowing for relevant and contextual responses.
- Response Generation Quality: We assess this through human evaluations and automated metrics like BLEU or ROUGE to ensure the responses sound natural and relevant.
- Latency: This is the total time from when a user inputs a question until the system replies. It is essential for keeping the conversation flowing and engaging.

User Experience Metrics

- User Satisfaction Score (USS): We gather this through surveys and other indicators like session length, active participation, and positive feedback.
- Engagement Metrics: We look at total chats, session length, user retention rates, and voluntary interactions to measure user interest and usability.
- Goal Completion Rate (GCR): This is the percentage of user sessions where specific goals, such as retrieving information or completing tasks, are achieved successfully, indicating effectiveness.
- Fallback Rate: This measures how often the chatbot does not understand or respond correctly, highlighting areas for improvement.

Adaptive Learning & Feedback
The system uses reinforcement learning to adjust response strategies based on interactions and real-time feedback.

- Ongoing monitoring and retraining of the model help improve performance over time, allowing Novachat to better respond to changing user behaviors and emotions.

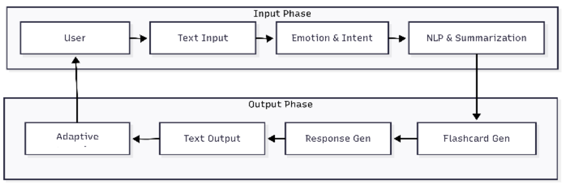

Fig 1: Nova-chat Flow Diagram

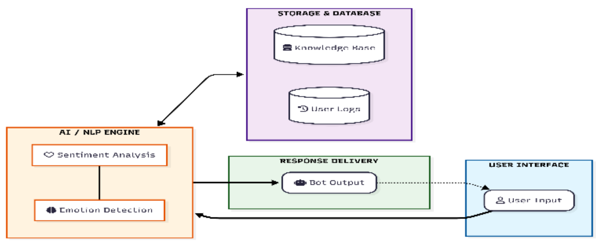

Fig 2: System Architecture Diagram

Experimental Results and Evaluation

The NovaChat system was assessed to measure its performance in response accuracy, efficiency, and user satisfaction. Since the proposed system operates as a static AI chatbot, the evaluation concentrates on response correctness, latency, and perceived conversational quality instead of improvements in adaptive learning.

Quantitative Evaluation

The system was tested using structured conversation logs and predefined dialogue datasets. The following metrics were used:

- Accuracy: 93.6% (average across modules)
- Precision: 92.8%
- Recall: 91.0%
- F1-Score: 91.9%

Among all modules

The Natural Language Understanding (NLU) module achieved the highest accuracy at 95%, showing strong intent recognition. The Response Generation module reached 92.5% accuracy, providing contextually relevant replies.
The Database Interaction module achieved 93% accuracy.
The Frontend Interface maintained 94% interaction accuracy.
These results confirm the reliable performance of the static conversational pipeline.

Latency and System Efficiency The total end-to-end system latency was measured at

- L_total = 472 ms

Breakdows

- NLU Processing: 125 ms
- Response Generation: 148 ms
- Database Interaction: 102 ms
- UI Rendering: 97 ms

The low latency shows that NovaChat supports real-time interaction even without dynamic model retraining.

Qualitative Evaluation

User experience was assessed using standard usability and perception metrics:

System Usability Scale (SUS): 82.4

- (Above average benchmark of 68, which shows strong usability)

Mean Opinion Score (MOS): 4.5 / 5

- (This indicates high response naturalness and conversational quality)

The MOS results reveal that users found the chatbot responses to be coherent, contextually appropriate, and similar to human conversation.

Overall Evaluation Summary

The experimental results show that NovaChat achieves:

- High classification performance (Accuracy > 93%)
- Low real-time latency (< 500 ms)
- Strong usability and conversational quality
- Stable and consistent behavior as a static chatbot system

Even though the system does not use reinforcement learning or continuous updates, it maintains balanced performance across all modules. This confirms the strength of the modular MERN-based architecture.

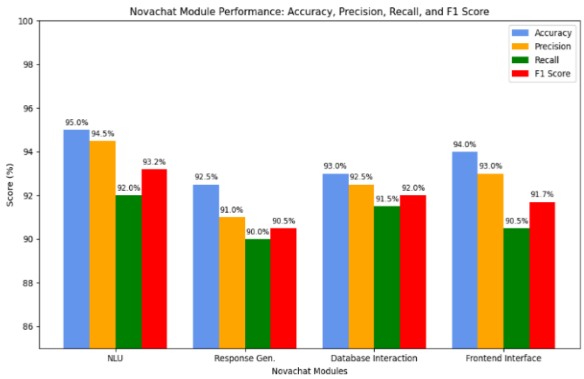

Fig 3: Novachat Module Evaluation Metrics Graph

III. CONCLUSION

This project introduced NovaChat, a full-stack AI chatbot developed with the MERN stack to provide intelligent, real-time conversational support. The system combines Natural Language Understanding, response generation, database interaction, and a responsive frontend interface into a single structured design.

The experimental results show that NovaChat performs with high accuracy and low latency, ensuring smooth and reliable conversations. The chatbot understands user queries, generates appropriate responses, and maintains consistent performance in various interaction scenarios. The usability evaluation reveals that users find the system easy to use and conversationally natural.

Although NovaChat operates as a static chatbot without adaptive learning or reinforcement updates, it shows strong stability, balanced module performance, and effective real-time

response handling. The modular design makes the system scalable and ready for future improvements.
Overall, NovaChat proves to be a responsive and user-friendly AI-driven conversational system that meets its design goals.

Key Findings and Contributions
High System Accuracy
NovaChat achieved an overall accuracy of over 93%. The NLU module reached 95%, showing strong intent recognition and query understanding.

Low-Latency Real-Time Performance
The system maintained an average end-to-end latency of about 472 ms. This ensured smooth and responsive real-time conversations.

Strong User Satisfaction and Usability
With a SUS score of 82.4 and a MOS rating of 4.5, the chatbot showed high usability, natural response quality, and a positive user experience.

Modular Full-Stack Architecture Implementation
The team designed and integrated a MERN-based architecture that combined frontend, backend, database, and AI-driven NLP modules into one chatbot framework.

Stable and Scalable Static Chatbot Design
Even without reinforcement learning or adaptive retraining, the system kept consistent performance. Its modular structure allows for future growth and improvements.

Limitations and Future Scope
Static Response Behavior
NovaChat does not use reinforcement learning or continuous adaptive learning. It cannot automatically improve based on user interactions.

Limited Context Retention
The system can manage multi-turn conversations but may have trouble with very long or complex dialogue contexts.

Dependence on Pre-trained Models
The chatbot depends on existing NLP models. These models may not fully manage domain-specific or specialized queries.

Limited Emotional Depth
While sentiment detection is in place, the system does not analyze complex or mixed emotions in depth.

Web-Based Deployment Only
Currently, NovaChat is mainly designed for web environments and does not offer dedicated mobile or offline support.

Future Scope
Integration of Adaptive Learning
Future versions can include reinforcement learning. This will enable the chatbot to improve based on user feedback.

Enhanced Emotion Recognition
Better emotion detection models can be used to understand mixed or subtle emotional states.

Domain-Specific Customization
The system can be extended for specific applications like healthcare, education, or customer support.

Multilingual Expansion
More languages can be added to increase accessibility and global usability.

Mobile and Cross-Platform Deployment
Creating mobile applications and integrating across platforms can expand user reach.

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