Real Time Chat Application with Emotion Detection through text

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***Abstract*— This literature review explores the current state of research on real-time chat applications that have integrated emotion detection capabilities. We analyze the studies published between 2018 and 2024, concentrating on three aspects: (1) innovations in real-time chat technology, with a focus on MERN stack-based developments; (2) methods of emotion detection in text-based communication; and (3) emotion detection integration within chat interfaces. Our survey indicates huge strides in deep learning models for the detection of emotion. Recent approaches have been able to show up to 91.5% accuracy. Along the journey, we identify some challenging areas such as real-time implementation issues, privacy issues, and user experience design. We conclude with future directions of research in this field: multimodal emotion detection, cross-lingual support, and ethical considerations in emotion-aware chat systems.**

Keywords—***Real-time emotion detection, chat applications, MERN stack, NLP, deep learning, AI.***

I. Introduction

Instant messaging with real-time chat applications transformed the way people communicated through a wide array of different networks. The emotion detection within such systems, within recent years, has been viewed as a landmark innovation in the human-computer interface of which affective computing falls as one of the top ones on the list. This has enabled emotions within textual messages and can make use of this emotional content in determining an interpretation to achieve contextual awareness and more empathetic understanding about users.

This literature survey paper particularly focuses upon the current state of research about emotion detection in real-time chat applications, especially with the MERN stack, which has gained importance for building scalable high-performance web applications. This study further discusses the different methodologies incorporating AI, ML, and DL techniques extensively used to get better accuracy as well as gain deeper knowledge about the contextual cues of emotions in text. This review condenses live studies concerning the chat applications that carried this emotion detection concept and answers the following questions:

- What's changing in live chat technologies, particularly those using the MERN stack MongoDB, Express.js, React.js, Node.js
- How are the emotion detection methods for text communication evolving?
- What are the challenges and solutions for integration into real-time chat interfaces?

In summary, this paper explores the state-of-the-art advancements in real-time chat applications integrated with emotion detection, highlighting the MERN stack's role, methodologies in AI-based emotion detection, and addressing challenges like real-time performance and user privacy.

1) An in-depth analysis of MERN stack and WebSocket technology for scalable chat applications.
2) Evaluation of various emotion detection techniques and their integration challenges.
3) Proposals for future research directions, including multimodal and cross-lingual emotion detection.

II. Literature Survey

A. Advancement in Real Time Chat Technologies

This section reviews the technological advancements and methodologies for real-time chat systems with emotion detection. It focuses on the implementation of the MERN stack and its advantages over traditional stacks.

1) MERN stack for Chat Applications: The MERN (MongoDB, Express.js, React.js, Node.js) stack has gained significant traction in developing real-time chat applications due to its scalability and performance. Kumar et al. [1] demonstrated that MERN-based applications could efficiently manage up to 10,000 concurrent users with an average latency of 45ms (±5ms). This performance surpassed traditional LAMP stack implementations, which showed degraded performance beyond 5,000 concurrent users. Zhang et al. [2] further enhanced MERN stack performance through novel caching mechanisms. Their approach reduced server response time by 40% compared to standard MERN implementations, handling up to 15,000 concurrent users with a latency of 38ms (±3ms). However, Johnson and Lee [13] argued that while MERN offers superior scalability, it may introduce complexity in deployment and maintenance, particularly for smaller applications.

A comparative study by Patel et al. [14] highlighted the trade-offs between MERN and MEAN (MongoDB, Express.js, Angular, Node.js) stacks for chat applications. They found that MERN outperformed MEAN in terms of rendering speed (MERN: 56ms vs MEAN: 72ms) and memory usage (MERN: 215MB vs MEAN: 258MB for 1,000 concurrent connections). However, MEAN showed better TypeScript support and more mature tooling.

2) WebSocket Technology: WebSocket technology has emerged as a crucial component for enabling real-time, bidirectional communication in chat applications. Li and Chan [3] demonstrated that WebSocket reduces server load by 70% compared to HTTP polling, with an average message delivery time of 32ms versus 102ms for long polling. Garcia-Molina et al. [15] introduced enhancements such as compression and encryption, optimizing WebSocket for chat systems. Their approach reduced data transfer by 45% and improved security without significant latency increase (average latency: 35ms, up from 32ms). However, Yamamoto and Nakamura [16] highlighted potential security vulnerabilities in WebSocket implementations, particularly in handling cross-origin requests. They proposed a modified WebSocket protocol that reduced successful cross-site scripting (XSS) attacks by 95% in their test scenarios.

B. Evolution of Emotion detection Techniques

1) NLP Technique: The emotion detection is based on text-based natural language processing techniques. One that has been most widely used is the NRC Emotion Lexicon [4], which provides a mapping of words onto eight basic emotions with 14,182 word-emotion associations.

Liu et al. [17] combined word embeddings along with linguistic features to achieve a better F1-score of 0.72 on the SemEval2019 dataset, a 7% improvement over pure lexicon-based approaches. On the other hand, Fernández-Gavilanes et al. [18] applied multilingual word embeddings in cross-lingual emotion detection with an average F1-score of 0.68 in 10 languages, reflecting the challenges in multilingual emotions analysis..

2) Machine Learning Approaches: Supervised machine learning techniques have been proven to be very effective for emotion detection tasks. Colneri and Demšar [5] achieved an accuracy of 86.3% with Random Forests on a Twitter dataset, outperforming SVMs (82.5%) and Naive Bayes classifiers (79.1%).

Zhu et al. [19] experimented with hybrid approaches that integrate traditional algorithms with attention mechanisms. Their model reached an F1-score of 0.89 on the SemEval-2018 dataset, outperforming the standalone machine learning techniques by 5%. Nevertheless, they reported a significant increase in the computational complexity and inference times of around 2.5 times more than traditional approaches.

3) Deep Learning Models: Deep learning models have significantly improved the accuracy of emotion detection. Zhang et al. [6] have used CNNs and LSTMs in achieving F1-score of 0.88 in the SemEval-2018 dataset. Li et al. [20] extended the performance of the above work using hierarchical attention networks, reaching F1-score of 0.90 on the same dataset.

Chen and Wang [21] introduced emotion-aware BERT techniques, achieving an F1-score of 0.915 on GoEmotions. However, they require computational costs that are orders of magnitude higher, consuming 300% more time in training models compared to traditional deep learning models.

A major controversy surrounding the model lies in the trade-off between complexity and real-time performance. While large, pre-trained models, say Chen and Wang [21], are supposed to be the ultimate winner, Wang et al. [8] argue that real-time application requires lighter and more domain-specific models, considering it imposes lower latency, 20ms vs 150ms for inference.

GANs have already been used in training the detection model with synthesized, emotively rich conversations. This method has significantly contributed to the ability to gauge faint emotions like sarcasm and empathy, Smith & Taylor, 2023 [31].

Transformer models using the attention mechanism have been applied to focus on portions of the conversations that have highly charged emotions and have surpassed previous results in detecting complex emotions, including sarcasm and frustration, Johnson & Wang, 2023 [32].

C. Integration Challenges and Solutions

1) Real-Time Performance: In real-time systems, introducing emotion detection brings trade-offs between accuracy and latency. Wang et al. [8] present dynamic model selection techniques that switch among multiple models based on message length and system load. Here, average latency is kept around 50ms and at the same time attains 85 percent of the accuracy level of the most complex model. Zhang et al. [22] discussed edge computing solutions, offloading emotion detection to user devices for messages under 50 words. This reduced server load by 60% and decreased average response time from 200ms to 80ms. However, Nakamura and Lee [23] argued that edge-based approaches might compromise privacy and model consistency, proposing a federated learning approach instead.

2) User Experience and Interface Design: Good visualization of detected emotions for good user experience. Lee et al. [9] reported that subtle cues such as color-coded messages are more liked than explicit labels where 78% of users reported a better understanding of the message tone without an increased cognitive load.

Patel and Srivastava [24] reported that animated emotion indicators increased user engagement by 15% in terms of average session duration. However, Kim et al. [25] cautions against the misuse of such emotion indicators as 22% of the users complained of being overwhelmed by too much emotional information.

3) Privacy and Ethical Considerations: Stark and Hoey [10] documented privacy issues associated with emotion detection systems, raising ethical issues related to consent and transparency. They noted that 65% of people would not like to be tracked at all times, and therefore they necessitate clear opt-in mechanisms.

Gao et al. [11] developed federated learning approaches in efforts to maintain user data while fine-tuning the detection models. Their method reduced data exposure by 99.5% compared to the centralized model while maintaining 95% accuracy, comparatively with the centralized model.

D. Limitations and Future Research Directions

1) Limitations of Current Research

a. *Dataset Bias:* Many studies rely on datasets predominantly in English, limiting generalizability to other languages and cultures. Chen et al. [27] found that models trained on English datasets showed a 20-30% drop in accuracy when applied to non-Western languages.
b. *Context Sensitivity:* Current models often struggle with context-dependent emotions, particularly in sarcasm and irony detection. Majumder et al. [7] reported a 15% drop in accuracy for context-dependent emotions compared to basic emotions.
c. *Real-world Validation:* Many studies are conducted in controlled environments, potentially overestimating real-world performance. Martinez and Johnson [26] found a 10-15% drop in accuracy when deploying lab-tested models in actual chat applications.
d. *Long-term Emotional Patterns:* Most current research focuses on instant emotion detection, neglecting long-term emotional trends in conversations. This gap was highlighted by Wang and Zhang [29], who argued for the importance of tracking emotional dynamics over time.

2) Future Research Directions

a. *Multimodal Emotion Detection:* Incorporating text, voice, and facial expressions could enhance accuracy. Liu et al. [28] demonstrated a 7% improvement in emotion detection accuracy using multimodal inputs compared to text-only models.
b. *Contextual Emotion Detection:* Considering conversation history and user profiles could improve accuracy in complex emotional scenarios. Hazarika et al. [12] showed promising results with a 10% improvement in detecting subtle emotions using contextual information.
c. *Cross-lingual Emotion Detection:* Supporting multilingual chat applications is crucial for global adoption. Chowdhury et al. [30] proposed a transformer-based approach for cross-lingual emotion detection, achieving an average F1-score of 0.76 across 5 languages, but noted significant challenges in emotion concept mapping across cultures.
d. *Explainable AI for Emotion Detection*: Increasing user trust through model interpretability is an important direction. Rodriguez et al. [31] introduced an attention visualization technique that improved user understanding of emotion predictions by 25%, but at the cost of a 10% increase in UI complexity.
e. *Ethical AI and Privacy-Preserving Techniques:* Addressing ethical concerns and enhancing privacy protection in emotion detection systems. Martinez and Johnson [26] proposed a differential privacy approach that maintained 90% of the original model's accuracy while providing strong privacy guarantees ($\varepsilon = 0.1$).

III. Applications

The integration of emotion detection in real-time chat applications presents a wide array of opportunities across diverse fields. Here follows an outline with elaborate details on the application thereof:

1) Customer Service and Support: Emotion detection in chat applications allows customer service representatives to gauge the emotional state of customers, enabling personalized and empathetic responses. For example, detecting frustration in a customer's tone can prompt the system to prioritize their queries or escalate the issue to a supervisor. Companies using this technology have reported improved customer satisfaction and resolution times.

2) Mental Health Support and Therapy: Emotion-aware systems can assist therapists and counselors in monitoring clients' emotional states during online sessions. Such applications are invaluable for crisis intervention, as they can detect signs of distress, sadness, or anxiety in real-time, alerting professionals to provide immediate support. For instance, chatbots integrated with emotion detection are being deployed in mental health helplines.

3) Social Networking Platforms: Social media platforms can enhance user interactions by offering emotional context within conversations. By visually representing emotions, such as through color-coded chat bubbles or animated emojis, users gain a clearer understanding of the conversational tone. This feature fosters meaningful connections while reducing misunderstandings.

4) Educational Platforms: In online learning environments, emotion detection helps educators adapt their teaching strategies based on student engagement levels. For example, detecting boredom or confusion in chat discussions allows teachers to modify their approach to maintain student interest and improve comprehension.

5) Team Collaboration and Productivity Tools: Emotion detection can enhance communication within workplace collaboration platforms. By identifying stress or conflict during professional discussions, these tools can help maintain a positive working environment and improve productivity. For instance, real-time emotion feedback can prompt managers to address potential issues before they escalate.

6) Human Resources and Employee Wellness: Emotion detection in chat applications provides insights into employee well-being, especially in remote or hybrid work setups. By analyzing conversational tones during virtual meetings or communication, HR professionals can identify early signs of burnout, stress, or disengagement, enabling timely interventions.

7) Healthcare Communication: In telemedicine and patient support, emotion-aware chatbots assist healthcare providers in understanding patients' emotional states, ensuring better communication and care delivery. For instance, identifying fear or confusion in patient messages can help doctors offer reassurance and clarity about medical procedures.

8) Online Dating and Relationship Platforms: By integrating emotion detection, dating platforms can improve user interactions by highlighting emotional tones in messages. This reduces misunderstandings and fosters more authentic connections, improving user satisfaction and engagement.

9) Market Research and Consumer Insights: Companies can use emotion detection in feedback systems and surveys to understand customer sentiments more accurately. Analyzing emotional responses to products, services, or advertisements provides actionable insights for improving offerings and marketing strategies.

10) Gaming and Virtual Reality: In a multiplayer game or a VR environment, emotion detection allows the relationship dynamics to be adapted for players' emotional states, which in turn makes it feel more immersive.

11) Legal and Mediation Services: Real-time emotion detection in mediation platforms helps moderators identify emotional cues, ensuring fair and empathetic conflict resolution. Legal professionals can also use this technology to gauge client emotions during consultations, improving service quality.

12) Government and Public Services: Emotion-aware chat systems can be deployed in public grievance redressal platforms to prioritize and address complaints effectively. Detecting distress or urgency in citizen messages allows governments to take timely actions.

IV. Result

The results demonstrate that hybrid deep learning models, such as those combining BERT with CNN, achieve the highest accuracy (91.5%) and F1-score (0.91) in emotion detection, albeit at the cost of higher computational demands. Comparative analysis shows that while traditional models like LSTMs offer lower accuracy, they are more computationally efficient, making them suitable for resource-constrained settings. Furthermore, the discussion emphasizes the trade-offs between model complexity and real-time applicability, highlighting the need for tailored solutions based on application requirements. Below is a more in-depth discussion:

A. Comparison of Models

1) CNN-LSTM Hybrid: This model achieved an accuracy of 89.5% and an F1-score of 0.88 on the SemEval-2018 dataset, making it highly effective for detecting emotions in English-language datasets. Its hybrid architecture leverages the spatial feature extraction of CNNs and the sequential learning capability of LSTMs. Despite its accuracy, the model requires optimization for real-time deployment due to computational overhead.

2) DialogueRNN: With an accuracy of 87.5% and an F1-score of 0.86, this model excels in analyzing conversational data sequentially. It effectively maintains contextual information across conversation turns, making it suitable for multi-turn dialogues. However, its real-time applicability is limited due to increased latency in processing sequential inputs.

3) Word Embeddings + Linguistic Features: Achieving an accuracy of 86.3% and an F1-score of 0.85, this approach demonstrates the potential of combining traditional word embeddings with linguistic features. It balances accuracy and computational efficiency, making it a viable option for real-time systems.

4) Cross-lingual Word Embeddings: Designed to support multilingual datasets, this method attained an accuracy of 84.7% and an F1-score of 0.83. Although slightly lower in performance compared to single-language models, its ability to detect emotions across multiple languages makes it indispensable for global applications.

5) Hybrid ML + Neural Attention: By integrating traditional machine learning techniques with neural attention mechanisms, this model achieved an accuracy of 90.2% and an F1-score of 0.89. The attention mechanisms enhance the model's ability to focus on emotion-rich portions of text, improving detection of subtle emotions like sarcasm and empathy.

6) Emotion-aware BERT: This state-of-the-art model reported the highest accuracy of 91.5% and an F1-score of 0.91 on the GoEmotions dataset. Leveraging BERT's contextual understanding and emotion-specific fine-tuning, the model offers unmatched precision. However, its high computational requirements pose challenges for real-time deployment.

B. Insights and Observations

1) Performance-Accuracy Trade-Off: While Emotion-aware BERT leads in accuracy, simpler models like Word Embeddings + Linguistic Features are more suitable for real-time applications due to lower computational demands.

2) Real-Time Capability: Models such as CNN-LSTM Hybrid and Hybrid ML + Neural Attention demonstrated good real-time potential but require optimization to reduce latency further.

3) Multilingual Support: Cross-lingual Word Embeddings provide an essential capability for multilingual systems, but further refinement is needed to close the performance gap with monolingual models.

4) Context Sensitivity: Models like DialogueRNN and Hybrid ML + Neural Attention excel in capturing context, making them ideal for applications requiring multi-turn conversational analysis.

C. Key Challenges Highlighted

1) Scalability: Highly advanced models like Emotion-aware BERT simply cannot provide throughput performance at the real-time level as they are slow; this is due to their complexity and computational intensity.

2) Dataset Diversity: The performance gap across languages and datasets suggests that reasonable and representative training data are required to ensure improved generalizability.

3) Latency vs. Accuracy: A balance between complexity of models and their response times is crucial for smooth integration into real-time systems.

D. Visualization

This comparative analysis presented in Figures 1 and 2 gives an overview of the performance trade-offs among models concerning accuracy and F1-score.

Figure 1 shows the accuracies for all models, with Emotion-aware BERT showing the best accuracy at 91.5%, followed very closely by Hybrid ML + Neural Attention at 90.2%. Traditional methods using Cross-lingual Word Embeddings performed with the least accuracy of 84.7%, demonstrating the trade-offs of gaining multilingual adaptability versus high precision.

Figure 2 compares F1-scores, where precision and recall are considered. Emotion-aware BERT is once again victorious with an F1-score of 0.91, which stresses the model's ability to provide accurate predictions while keeping false positives and negatives low. Other models closely follow, CNN-LSTM Hybrid & Hybrid ML + Neural Attention, with scores of 0.88 and 0.89, respectively, placing them as contenders for real-time applications with balanced performance and computational efficiency.

Table 1: comparison of methods for emotion detection in chat applications.

Model	Accuracy	F1-Score	Dataset	Language Support	Real-time Capability
CNN-LSTM Hybrid [6]	89.5%	0.88	SemEval-2018	English	Yes
DialogueRNN [7]	87.5%	0.86	IEMOCAP	English	Limited
Word Embeddings + Linguistic Features [	86.3%	0.85	SemEval-2019	English	Yes

17]					
Cross-lingual Word Embeddings [18]	84.7%	0.83	Multilingual Twitter Corpus	10 languages	Yes
Hybrid ML + Neural Attention [19	90.2%	0.89	SemEval-2018	English	Yes
]					
Emotion-aware BERT [21]	91.5%	0.91	GoEmotions	English	Limited

Fig. 1. Model Accuracy Comparison

Fig. 2. Model Accuracy Comparison

E. Future Scope in Results Analysis

Future work will be concentrated on making the emotion-detection approach more accurate and robust in a multilingual and cross-cultural environment. In addition, multimodal inputs such as voice and facial recognition would enhance the contextual understanding of the scene. There will also be the need to focus on ethical AI and federated learning to solve the issues of privacy. Advancement in lightweight models for edge devices will provide better real-time performance.

F. Conclusion

In this study, we highlight the critical advancements in real-time chat applications and emotion detection systems. The MERN stack, in combination with WebSocket technology, has proven effective for developing scalable and high-performing chat systems. Furthermore, emotion detection in chat applications has significantly benefited from advancements in NLP, machine learning, and deep learning techniques. Approaches such as GANs and transformer models have enhanced the detection of subtle and complex emotions in real-time interactions.

However, integrating these technologies into real-time systems presents challenges, particularly in maintaining a balance between accuracy and system performance. Edge computing and lightweight models offer promising solutions for minimizing latency and improving resource utilization. In terms of user experience, the way emotions are displayed in chat interfaces plays a crucial role in user satisfaction, with subtle and adaptive visual cues proving more effective. Privacy and ethical concerns must be prioritized, particularly with the increasing use of emotion AI in communication technologies. Federated learning and transparent systems are essential for safeguarding user data while maintaining system effectiveness. Future research should focus on multimodal emotion detection, cross-lingual support, and explainable AI to create more robust, user-friendly, and ethical real-time chat systems.

G. Proposed Work

The proposed work focuses on developing a real-time chat application integrated with emotion detection through text based on advanced AI and ML techniques. The frontend will be designed with React.js so that it provides a very user-friendly and interactive chat interface. This interface will enable seamless, real-time communication by incorporating WebSockets to update messages instantly. Additionally, the chat window will show detected emotions as visual cues such as icons or text (e.g., "Happy" or "Sad") right below each message, thereby improving user experience and emotional context.

The backend will implement the real-time data processing using Node.js with Express.js. A secure MongoDB database will be used to hold chat history and corresponding detected emotions. The backend will also include authentication and session management to ensure data security and user privacy.

The emotion detection module is a critical component of the system. A machine learning model will be trained on emotion-labeled datasets, such as Sentiment140 or GoEmotions, to classify emotions in text messages. This module would make use of NLP techniques including tokenization, lemmatization, and stopword removal, which would extract meaningful features from user messages. Advanced deep learning architectures, including LSTM or BERT, would be used to power emotion classification to ensure accurate emotion detection. The trained model will be deployed through a Flask or Django API, which will enable real-time prediction and integration with the chat application. This cohesive architecture, comprising a dynamic frontend, robust backend, and powerful emotion detection module, will ensure a seamless and enhanced communication experience by bridging the gap between textual messages and their emotional context.

Fig.3 Flow diagram of proposed work

Acknowledgment

The We would like to express our deepest gratitude to Dr. Mukesh Azad sir for his invaluable guidance, constant support, and encouragement throughout this research. His insights, expertise, and constructive feedback have been instrumental in shaping the direction of this work. We are extremely fortunate to have had the opportunity to learn from him, and his mentorship has been pivotal in overcoming challenges and achieving our objectives.

We also extend our sincere thanks to **Samrat Ashok Technological Institute, Vidisha,** for providing the essential resources, infrastructure, and a conducive environment for research and learning. The support from the institute has played a crucial role in the successful completion of this project. Additionally, we are grateful to our peers and collaborators whose feedback and discussions have helped refine our ideas and approaches. Their involvement has been an enriching part of this journey, and we appreciate their contributions to the research process. Lastly, we acknowledge all the researchers and authors whose prior work has laid the foundation for this study and inspired us throughout our research.

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