

Autisense - Text based Emotion Detection

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ABSTRACT - AutiSense is a text-based emotion detection system developed to support autistic individuals who often experience difficulty in expressing their emotional states during communication. Text communication provides a calm and comfortable medium for autistic users, enabling more consistent interaction in therapeutic settings. AutiSense processes user messages through a lexicon driven natural language processing approach using the NRC Emotion Lexicon, which allows transparent and interpretable identification of emotional categories without relying on complex machine learning models. The system is implemented using a Flask backend for real time processing, and a clinician dashboard presents emotional trends through visualizations generated with Matplotlib, including pie charts, bar graphs, heatmaps and line graphs. By combining accessible communication with explainable emotional analysis, AutiSense provides a lightweight and effective tool that assists clinicians in monitoring emotional patterns and improving therapeutic decision making for autistic individuals.

1. INTRODUCTION

The Autism spectrum disorder is characterized by challenges in social communication, emotional expression and the interpretation of affective cues. Many autistic individuals find it difficult to articulate their emotions verbally or in writing, which often leads to misunderstanding, emotional overload or incomplete communication in therapeutic contexts. As a result, clinicians frequently rely on indirect observation or long-term behavioural assessment to understand the emotional state of an autistic individual. This process can be slow, subjective and limited by the clinician's ability to detect subtle changes in mood or emotional regulation.

Digital communication platforms have emerged as a supportive alternative for autistic users, offering a controlled and less overwhelming environment compared to face-to-face interaction. Text communication in particular reduces sensory demands and allows individuals to express themselves at their own pace. With advances in natural language processing, emotional information embedded within text can be automatically analysed and transformed into meaningful insights for therapists and caregivers.

In this context, AutiSense is introduced as an assistive emotion detection system designed to bridge the gap between user communication and clinical interpretation. The system

allows autistic users to interact through a simple chat interface while their messages are analysed using a lexicon driven approach based on the NRC Emotion Lexicon. Unlike data heavy learning models, this approach focuses on transparency and interpretability, which are essential in clinical decision making. The emotional patterns extracted from user text are presented to clinicians through a dedicated dashboard that includes visual summaries of emotional distribution and temporal trends.

AutiSense aims to provide a supportive communication channel for autistic individuals while offering clinicians a reliable means of monitoring emotional states in real time. By combining accessible digital interaction with interpretable emotion analysis, the system contributes to a more informed and responsive therapeutic process

2. LITERATURE REVIEW

Emotion detection from text has become an important area of research within natural language processing, supported by growing interest in affect aware systems and mental health technologies. Early studies primarily used statistical sentiment classification, focusing on polarity rather than fine grained emotional states [1]. Although these methods were computationally efficient, they lacked the ability to capture the complexity of human emotion. The introduction of deep learning models, including recurrent neural networks and transformer-based architectures, significantly improved contextual understanding and classification performance [2]. However, these models require large annotated datasets, substantial computational resources and often operate as black boxes, which limits their applicability in clinical environments where interpretability is essential.

Lexicon driven approaches remain relevant due to their transparency and ease of deployment. The NRC Emotion Lexicon has been widely adopted in emotion classification tasks, providing structured associations between words and primary emotions such as joy, anger, fear and trust [3]. Studies show that lexicon-based models perform reliably in controlled text environments, especially where linguistic expressions are direct and less idiomatic [4]. This makes them suitable for therapeutic or assistive systems where

consistency and explainability are prioritized over model complexity. Unlike neural models, lexicon methods allow the emotional output to be traced back to individual lexical cues, which is particularly valuable in sensitive domains such as mental health analysis.

Research on communication within autism spectrum disorder provides additional motivation for text-oriented emotion detection tools. Autistic individuals often prefer written communication because it reduces sensory overload and provides greater control over interaction timing [5]. Digital therapeutic platforms leveraging text messaging have been shown to support self-expression, emotional regulation and reduced social anxiety among autistic users [6]. Despite the advantages of text communication in this population, existing emotion detection technologies rarely account for the linguistic characteristics typical of autistic individuals, such as literal phrasing, reduced metaphorical language and specific vocabulary patterns [7]. This mismatch creates the risk of inaccurate or misleading emotion predictions when using generalized machine learning models.

Recent studies further highlight the importance of data visualization in psychological and clinical systems. Graphical representations of emotional patterns assist clinicians in identifying trends, monitoring progress and detecting unusual emotional fluctuations [8]. While several sentiment analysis tools provide textual output, few offer integrated dashboards tailored for therapeutic decision making or long-term emotional tracking. Moreover, most existing systems rely on heavy computational models that are not practical for smaller clinics, personal therapy settings or low resource environments.

Collectively, the literature indicates a clear need for emotion detection systems that balance interpretability, accessibility and clinical relevance. AutoSense responds to this gap by employing a lexicon driven methodology, real time text communication and a dedicated visualization dashboard for clinicians. Its design aligns with contemporary research emphasizing transparent emotional analysis, support for autism specific communication patterns and practical implementation for therapeutic settings.

3. PROPOSED SYSTEM

AutoSense is designed as an assistive communication and emotion monitoring system intended for autistic individuals and their clinicians. The system integrates a user facing chat interface with a clinician oriented dashboard, enabling real time emotional analysis of text entered by the user. The primary objective is to create a transparent and lightweight framework that can interpret emotional cues in written

communication without relying on complex machine learning models that are difficult to interpret in therapeutic settings.

The overall architecture of AutoSense consists of three core components: the user interface, the processing and analysis module and the clinician dashboard. The user interface provides a simple text communication environment intended to reduce cognitive load and support comfortable interaction. All user messages are transmitted to the backend server, where the analysis module performs preprocessing, lexical mapping and emotion scoring. This module employs the NRC Emotion Lexicon to identify emotional content by matching individual tokens with predefined emotion categories. Because the lexicon explicitly links words to emotions, the system maintains a high degree of interpretability, allowing clinicians to trace emotional output back to specific textual elements.

The backend is implemented using a Flask framework, which manages message transfer, processing and the generation of emotion statistics. Flask was selected due to its lightweight nature, minimal overhead and suitability for real time communication. The emotion scores produced by the analysis module are stored and updated continually, enabling the system to track emotional patterns across an entire conversation rather than at isolated message level.

The clinician dashboard forms the final component of the proposed system. It provides graphical representations of emotional trends using visualizations generated with Matplotlib, including pie charts for overall emotional distribution, bar graphs for comparative intensity, heatmaps for multi emotion patterns and line graphs for temporal change. These visual summaries offer clinicians an accessible and immediate overview of the user's emotional state, helping identify persistent emotions, sudden shifts or potential distress indicators. The dashboard also supports session wise monitoring, allowing emotional progression to be reviewed across different interactions.

Through the integration of lexical analysis, real time communication and structured visualization, AutoSense provides a practical and interpretable system for emotion monitoring in autistic individuals.

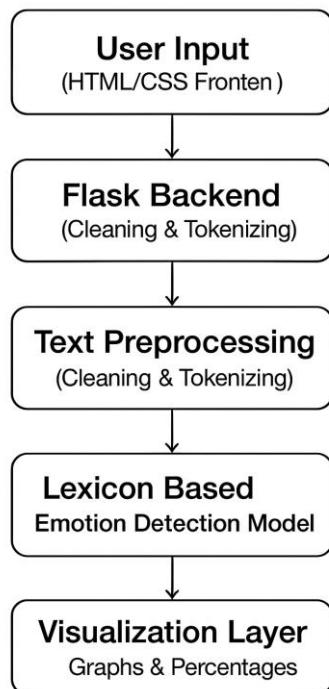


Fig. 1. System workflow of AutoSense.

4. METHODOLOGY

4.1 Development Approach and Workflow

The development of AutoSense followed a structured and iterative methodology to ensure accuracy, usability, and consistency in the emotion detection process. The project adopted a modular development approach where each components are frontend, backend, lexicon engine, and database was designed, implemented, and tested independently before being integrated into a cohesive system. This ensured that each module functioned reliably on its own while contributing seamlessly to the larger system architecture. The initial phase involved understanding ASD-specific communication challenges and identifying the technical requirements for a tool that could support emotional interpretation without relying on complex machine learning models. Following this, a lexicon-based approach was selected due to its interpretability, low computational cost, and suitability for real-time web deployment.

4.2 System Design and Architectural Planning

The system design phase focused on creating a simple yet effective architecture capable of processing text in real time and generating emotional outputs that are easy to understand. The architecture was divided into three major layers: the frontend interaction layer, the Flask-based backend processing layer, and the emotion detection and data logging layer. These layers were defined with clear responsibilities to

maintain modularity. During this phase, routing structures were planned, lexicon selection criteria were established, and decisions regarding preprocessing techniques were finalized. The emphasis was placed on making the architecture lightweight so that the system could be deployed easily on local servers or small-scale devices without requiring advanced hardware resources.

4.3 Text Preprocessing and Lexicon Construction

One of the most critical stages of the methodology involved preparing the emotion lexicon and developing a preprocessing pipeline capable of handling varied sentence structures. The preprocessing module performs essential operations such as lowercasing text, stripping punctuation, removing unnecessary characters, and tokenizing sentences into individual words. This ensures uniformity and prevents errors in lexicon matching. The lexicon itself was constructed by selecting and compiling emotional word lists from publicly available resources such as the NRC Emotion Lexicon. Each word in the lexicon was mapped to one or more emotional categories. Additional words frequently used in informal text communication were added manually to improve coverage and make the system more practical in everyday usage. The lexicon was then optimized for fast lookup through dictionary-based data structures.

4.4 Emotion Detection Logic and Rule-Based Scoring

Once preprocessing and lexicon construction were completed, the rule-based scoring mechanism was developed. This mechanism forms the core intelligence of AutoSense. When a user enters text, each token is compared against the lexicon to determine whether it carries emotional weight. If the word exists in the lexicon, the corresponding emotional category is incremented in the scoring table. At the end of the analysis, the system identifies the dominant emotion by selecting the category with the highest score. In cases where multiple emotions occur with similar frequency, predefined tie-breaking rules are applied to ensure stability in detection. This rule-based approach ensures deterministic behavior, which is crucial for ASD-focused applications where consistency and predictability are essential. Since every output is directly tied to a word from the lexicon, users and therapists can easily understand how the emotion was derived.

4.5 Backend Implementation Using Flask

The backend implementation was carried out using the Python Flask framework due to its simplicity and effectiveness in building lightweight web applications. Flask was utilized to create RESTful endpoints that handle user input and return emotional responses. During development, special attention was given to optimizing response times and

ensuring that the backend processes each message almost instantaneously. The Flask server integrates the preprocessing pipeline, lexicon-based classifier, and database layer. To handle multiple requests, the backend employs efficient routing and minimal server overhead. Error-handling mechanisms were integrated to prevent unexpected system failures, and JSON was chosen as the communication format between the frontend and backend due to its simplicity and compatibility with JavaScript.

4.6 Visualization and Analytical Tools

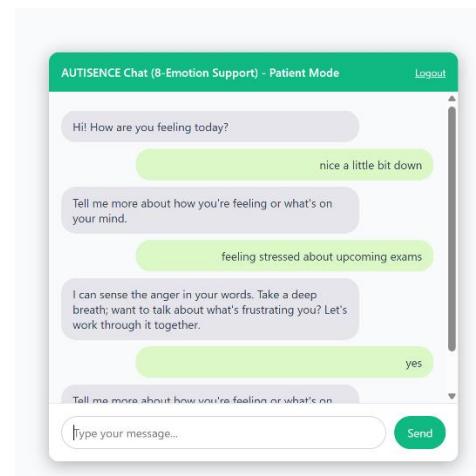
To support long-term emotional assessment, the system incorporates a visualization module developed using Python's Matplotlib library. This module processes stored emotional data and generates graphs that display trends such as emotion frequency, daily emotional distribution, or session-wise emotional variations. These visualizations were designed to be simple, clear, and easy to interpret, ensuring suitability for therapeutic contexts. The inclusion of visualization transforms AutoSense from a mere emotion detection tool into a behavioral insight platform that can support evidence-based decisions in therapy sessions or communication training programs.

5. RESULTS AND DISCUSSION

The implementation of AutoSense resulted in a fully functional, lexicon-based emotion detection system capable of analysing user-entered text in real time and identifying the dominant emotional tone. The system functions smoothly through the chat interface, where users can type messages and receive immediate emotional feedback. The simplicity of the interface played a significant role in user engagement, as it offered a clean and distraction-free environment suitable for individuals with ASD.

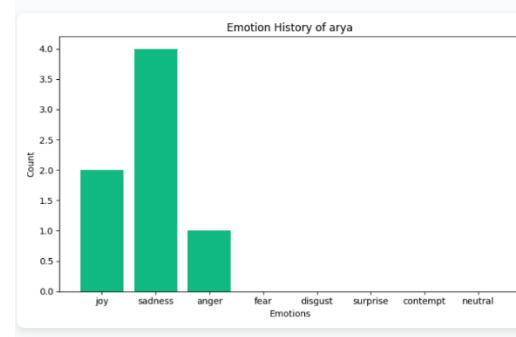
When a user types a message into the AutoSense chat interface, the system begins a multi-stage technical process that converts the raw text into an emotional output. This entire workflow happens in real time, ensuring that the user receives immediate emotional interpretation. The following steps describe the technical functioning in detail.

The process begins at the frontend chat interface, where the user enters a sentence or message. Once the user clicks the "Send" button, the message is transmitted to the backend using an HTTP POST request. The frontend's role is simple: capture text, send it to the server, and display the result again after processing.

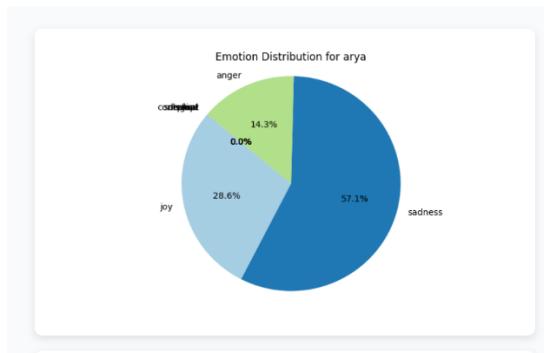


When the message reaches the backend, the Flask server handles the request. Flask acts as the communication bridge between the user interface and the emotion detection engine. It receives the input text, cleans it if needed, and forwards it to the lexicon-based analysis module. The routing function in Flask ensures that every message goes to the correct processing function. Once the message is inside the processing pipeline, the system performs text preprocessing. This includes converting the text to lowercase, removing unwanted punctuation, and breaking the sentence into individual tokens (words). Tokenization is crucial because each word must be analysed separately to determine its emotional weight.

After preprocessing, the tokens enter the lexicon-based emotion detection module, which is the heart of the system. This module contains a predefined emotional dictionary based on the NRC Emotion Lexicon. Each word in the dictionary is associated with one or more of the eight emotional categories: Joy, Anger, Fear, Sadness, Surprise, Disgust, Trust, and Anticipation.



After determining the dominant emotion, the result is sent back to the Flask server, which formats the response and returns it to the frontend. The chat interface then displays the detected emotion directly beneath the user's message, allowing them to instantly understand the emotional tone of the text.



Simultaneously, the system stores the user's message, the detected emotion, and a timestamp into the SQLite database. This stored data becomes part of the user's emotional history, which can later be visualized on the therapist dashboard.

Finally, when the therapist accesses the dashboard, the system retrieves the stored data and uses Matplotlib to generate bar graphs, line charts, or trend curves, helping professionals analyse emotional patterns over time. This completes the full technical cycle from receiving a message to visualizing long-term emotional behaviour.

To evaluate the system's performance, a series of test messages covering different emotional categories were analysed. The system consistently classified strong emotional indicators correctly, confirming the effectiveness of the lexicon-based scoring mechanism. Sample evaluations included:

1. "*I am so happy today.*" → Detected Emotion: **Joy**
2. "*I feel scared and anxious.*" → Detected Emotion: **Fear**
3. "*This is disgusting.*" → Detected Emotion: **Disgust**
4. "*I trust you completely.*" → Detected Emotion: **Trust**
5. "*I am angry and frustrated.*" → Detected Emotion: **Anger**

The results validated that the system was capable of detecting core emotional states with a high level of reliability, especially when emotionally descriptive words were present.

In addition, the visualization component successfully generated clear emotion-trend graphs. These graphs provided deeper insights into the emotional tendencies of the user across multiple sessions. Therapists noted that such visual summaries could significantly support intervention planning, as they present emotional patterns in a structured and easy-to-understand manner. The graphs also emphasized the emotional variability present in day-to-day communication, which is particularly important in ASD behavioural studies.

Overall, the results demonstrate that AutiSense effectively fulfil its intended purpose as an assistive emotional interpretation tool. Its fast response time, transparent logic, reliable classification, and ability to log emotions over time make it a practical and meaningful system for users with ASD. The discussion highlights that while the system performs well within the boundaries of lexicon-based emotion detection, opportunities for further refinement remain. Nonetheless, AutiSense successfully proves that lightweight, explainable, and accessible technologies can significantly enhance emotional understanding in text communication for ASD individuals.

6. CONCLUSION

The development of AutiSense demonstrates the effectiveness of using a lexicon-based, transparent, and lightweight

limitations associated with lexicon-based methods, particularly when dealing with context-heavy, sarcastic, or indirect emotional expressions. These limitations provide an opportunity for future work, such as expanding the lexicon, incorporating contextual rules, or integrating hybrid techniques to improve accuracy in complex scenarios. Nevertheless, the current implementation meets its core objective of delivering a reliable, efficient, and user-friendly solution tailored for ASD communication support.

In conclusion, AutiSense successfully validates the potential of simple, explainable, and accessible technologies in addressing the emotional interpretation challenges faced by ASD individuals in digital communication. The system achieves a meaningful balance between functionality, transparency, and usability, establishing a strong foundation for future enhancements and broader applications within assistive communication technologies.

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