Mental Health Tracker for Mute Community using Sign Language

Dr Soma Prathibha
Department of Information Technology
Sri Sairam Engineering College
Chennai, India
prathibha.it@sairam.edu.in

Jothika S
Department of Information Technology
Sri Sairam Engineering College
Chennai, India
jothika1407@gmail.com

Dharshini S
Department of Information Technology
Sri Sairam Engineering College
Chennai, India
dharshinisiva2603@gmail.com

ABSTRACT

In the modern world, mental health concerns persist as a significant challenge, impacting millions of individuals across the globe. Although commendable progress has been achieved in terms of raising awareness, reducing the stigma associated with mental health, and enhancing access to treatment, there are enduring obstacles stemming from insufficient resource allocation, societal pressures, and the pervasive influence of digital technologies. To ensure a healthier future, it is imperative that we maintain an unwavering commitment to prioritize mental health, strengthen support systems, and encourage open and candid conversations. Within this intricate landscape, the mental well-being of the mute community necessitates special attention due to the unique communication barriers they face. It is essential to establish tailored support mechanisms, incorporating visual aids and alternative modes of communication. Here, technological innovation, particularly in the realm of data science, emerges as a potent tool to address these challenges. Data-driven methodologies play a pivotal role in converting sign language into comprehensible forms, such as text and spoken language, transcending linguistic barriers and fostering inclusivity for the mute community. At the heart of this visionary system lies a commitment to understanding and addressing the emotional states of mute individuals. Leveraging the power of data and technology, this system endeavors to conduct sentiment analysis on non-verbal cues and expressions, surpassing conventional communication boundaries. By deciphering gestures, facial expressions, and body language, it aims to provide valuable insights into the emotional well-being of mute individuals. These insights will be consolidated into comprehensive weekly reports, offering substantial emotional support to those who need it most.In conclusion, this innovative approach promises to have a substantial impact on mental health support for the mute community. By combining sign language conversion with sentiment analysis, it offers a holistic solution that not only bridges communication gaps but also nurtures emotional well-being among mute individuals, ultimately contributing to a brighter and more inclusive future for all.

Keywords: **Mental Health, mute community, communication barriers, data-driven innovation, sentiment analysis, emotional well-being, sign language conversion, inclusivity, support systems, societal pressures, mental illness, stigma reduction, resource allocation, technological innovation, comprehensive reports.**

I. INTRODUCTION

Mental illness continues to loom as a pressing concern within contemporary society, casting its shadow over millions worldwide. Although we have made notable strides in fostering greater awareness, mitigating stigma, and improving access to treatment, formidable challenges persist. Inadequate resource allocation, the relentless weight of societal pressures, and the ever-pervasive influence of the digital realm remain formidable hurdles. To forge a path toward a healthier future, sustained efforts are imperative. Prioritizing mental health, bolstering support systems, and fostering candid conversations must remain at the forefront of our collective mission.Within this intricate landscape, we must exercise heightened vigilance and care when considering the mental well-being of the mute community. The potential communication barriers they face demand our utmost attention and dedication. It is incumbent upon us to champion specialized support mechanisms, replete with visual aids and alternative modes of communication, as a top priority. By tending to their emotional needs, reducing the pernicious grip of isolation, and championing accessible mental health services, we can pave the way for a brighter future for this community. Fostering meaningful connections and reducing isolation for those with communication barriers, a mental tracker is a vital tool enabling the expression of emotions. It also paves the way for personalized support, offering insights into the emotional states of mute individuals, fostering a deeper understanding of their needs. The primary goal is to develop a system that translates sign language into understandable text and spoken language, easing communication and alleviating the sense of isolation. Simultaneously, the project raises awareness about the mental health challenges faced by the mute community, empowering them to express themselves effectively, boosting self-confidence and overall well-being. This initiative promotes open discussions about mental health, making support and communication accessible to mute individuals. It also includes the development of an emotion analysis system, enabling them to articulate feelings and receive appropriate support. Weekly reports provide valuable insights into mental health trends within the mute community, ensuring their unique needs are recognized and addressed, leading to a more inclusive future for all. In the realm of technological innovation, data science emerges as a potent force, uniquely positioned to address the communication challenges faced by the mute community. Data-driven methodologies play a pivotal role in converting sign language into comprehensible forms for humans, including text and spoken language , across a spectrum of languages. Machine learning algorithms, aptly trained on sign language datasets, discern and decipher intricate patterns, ultimately facilitating accurate translation into text. This transformative approach not only enhances communication accessibility but also champions the cause of inclusivity for the mute community. In light of these considerations, our visionary system, now proposed, aspires to transcend the boundaries of traditional communication. Its primary mission is converting the intricate sign language utilized by the mute community into forms intelligible to all, encompassing text and spoken language in diverse linguistic dimensions, all thanks to the prowess of data science. Beyond this remarkable feat, the system sets out to unravel the enigmatic emotional states of mute individuals through the art of sentiment analysis. By harnessing the power of data and technology, it endeavors to generate a comprehensive weekly report, poised to deliver in-depth insights and unwavering support to those who need it most.

II. LITERATURE SURVEY

Ajitha et al. outline the development of a sentiment analysis tool that employs feature extraction and machine learning methods in [1]. They deal with the design of sentiment analysis tools, as well as feature extraction and machine learning techniques.p The disadvantage is that they did not specify the approaches and algorithms used for feature extraction.

Zhou et al. investigate implicit sentiment analysis in [2] by concentrating on event-centered text representation. They look into implicit sentiment analysis and event-based text representation. The downside was that they lacked event-centered representation-specific techniques and approaches.

Mishra et al. describe a data extraction method that uses natural language processing for sentiment analysis in [3]. They address data extraction with NLP for sentiment analysis and provide a data extraction approach.
They did not go into detail about the NLP approaches and methodologies employed for data extraction.

Banerjee et al. investigate the impact of cultural transitions on multimodal sentiment analysis in [4]. They investigate the impact of cultural transitions on sentiment analysis; they concentrate on multimodal analysis. There are no detailed cultural-shift detection tools.

Nandwani et al. give an overview of sentiment analysis and emotion identification from text in [5]. The specific sentiment analysis techniques will not be covered in detail.

Tan et al. [6] present a hybrid model for sentiment analysis (RoBERTa-LSTM) that combines transformer and recurrent neural network (LSTM) techniques. There is no specific training or model tuning information supplied.

Addepalli et al. explore converting American Sign Language to text using deep learning for feature extraction and Naive Bayes for classification in [7]. Deep learning architectures and training procedures are not discussed in detail.

Sachan et al. rely on sentiment analysis to classify code-mixed bilingual phonetic text in [8]. The specific strategies for code-mixed text categorization are not thoroughly addressed.

Hauffa et al. characterise social ties using sentiment analysis and natural language processing (NLP) in [9]. The procedures for sentiment analysis are not thoroughly discussed.

Zhang et al. present BMT-Net, a wide Multitask Transformer network for sentiment analysis, in [10]. There are no unique architectural details or training methods.

Velampalli et al. compare sentiment analysis performance on text and emoji data using various AI models in [11]. There are no particular AI model setups or evaluation criteria.

Abubakar et al. describe an improved feature acquisition method for sentiment analysis of English and Hausa tweets in [12]. There are no specific strategies for acquiring features. It concentrated on two languages (English and Hausa).

Barnes et al. investigate structured sentiment analysis as dependency graph parsing in [13]. There are no defined parsing strategies, and the algorithms may be vague.

Tesfagergish et al. talk about zero-shot emotion detection for semi-supervised sentiment analysis using Sentence Transformers and ensemble learning in [14]. There are no particular ensemble learning methodologies or Sentence Transformer setups.

Alexandridis et al. present insights into sentiment analysis and opinion mining in Greek social media in [15]. It concentrates on a specific language (Greek); sentiment analysis techniques are not addressed in full.

III. METHODOLOGY

The proposed project aims to improve sign recognition and communication for the mute community using a camera-based assistive system implemented on a Raspberry Pi. This section outlines the detailed project methodology, including the existing system analysis, the advantages of the proposed system, and hardware and software requirements. In the existing system, the use of KNN (K-Nearest Neighbors) and SVM (Support Vector Machine) algorithms is prevalent for sign recognition. However, these methods have limitations, including the low range of analogy output from flex sensors and difficulties in finding optimal gradients for accurate sign detection. Additionally, poor edge detection further hinders the effectiveness of the system.

The proposed system introduces a camera-based approach, enhancing the accuracy and efficiency of sign recognition and communication for the mute community. The system employs a camera for sign recognition, allowing for more accurate feature extraction. This, in turn, enables improved recognition of signs used in communication. For each recognized sign, the system is designed to trigger specific functions such as audio output or text output. This feature enhances the practicality of the system in assisting the mute individuals. The new system benefits from reduced algorithm complexity compared to the existing one. This simplification enhances the efficiency of the sign recognition process. The proposed system ensures low processing time, ensuring quick response and communication for the users.

Hardware Requirements:

The hardware components essential for the successful implementation of this project include:

Raspberry Pi: The central processing unit, responsible for sign recognition and triggering functions.

USB Camera: The camera is used for capturing sign gestures, which are then processed by the system.

SD Card: An SD card is used for data storage and system operation.

Monitor: A display unit is essential for visual feedback and system interaction.

Audio Output Unit: This unit is responsible for generating audio outputs when specific signs are recognized.

Software Requirements:

The software requirements for the project encompass:

Programming Language: Python is the primary programming language used for coding and development.

Development Platform: Python 3 IDLE serves as the development platform for coding the project.

Raspberry Pi OS: The Raspberry Pi is operated using the Raspbian OS, a customized operating system designed for Raspberry Pi boards.

Library: OpenCV, a widely-used computer vision library, is incorporated for image processing and sign recognition.

During the development phase, Python code is authored and rigorously tested to enable the Raspberry Pi to capture sign language gestures via the USB camera. The code also processes the captured images, recognizing signs accurately. The system excels in recognizing specific signs and mapping them to predefined functions. Users can configure this mapping to execute actions like generating audio output or displaying text. This user-configurability fosters personalized communication. An intuitive user interface is designed to display recognized signs and execute functions. Users receive visual feedback through a connected monitor, and audio output is also available. After successfully converting sign language to text, the system extends its capabilities to analyze text and detect facial expressions. Emotions such as happiness, sadness, and anger are discerned through image processing and text analysis. In instances where negative emotions are detected by the system, an alerting mechanism is initiated. IoT sensors facilitate communication with caregivers or designated contacts, ensuring they receive alerts and notifications regarding the user's emotional state. Refer figure 3.1

Formulas and Equations:

Emotion Detection:
Emotion Score = f(facial expressions, text analysis)

Alerting System:
If Emotion Score ≤ Threshold:
Trigger Alert

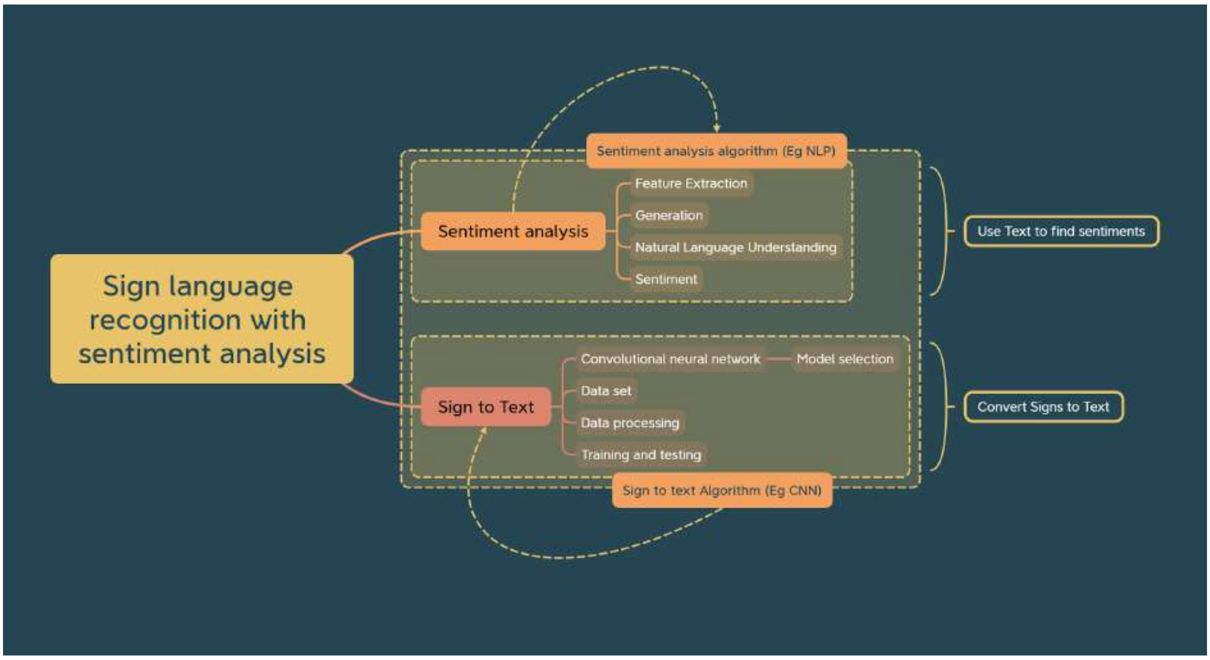

Fig 3.1 Architectural Diagram

Comprehensive testing is conducted to validate the system's performance in sign recognition, function execution, emotion detection, and the alerting system. Real-world scenarios involving proficient sign language users are simulated to assess the system's efficiency and effectiveness. Based on test results, adjustments and optimizations are made to enhance the system's accuracy, response time, and overall performance. Extensive documentation, including user manuals, is created to aid users and future developers in comprehending and utilizing the system. The system is deployed in mute schools and related institutions. Continuous maintenance and support are provided to ensure sustained functionality and relevance.

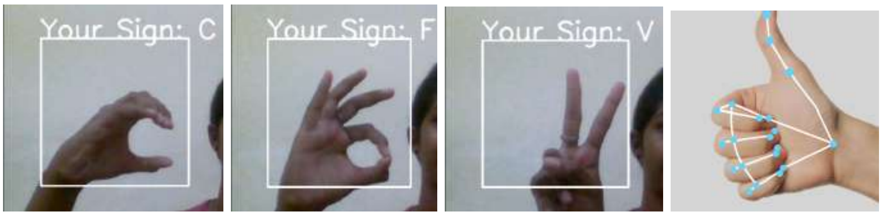

Fig 3.2 Sign Language Recognition

IV. CONCLUSION

In conclusion, our research project has effectively used the Raspberry Pi and machine learning techniques to address the crucial issue of mental health monitoring. We have successfully interpreted sign language's representations of mental health, ensuring inclusivity for people with speech and hearing impairments. In the future, we intend to develop our system by adding a psychiatrist suggestion tool and custom daily routines to support mental health.

The findings of our experiment point to the possibility of a revolutionary development in mental health support, where technology combines with conventional treatment to provide all-inclusive solutions. We envision a time when people can effectively manage their mental health thanks to the seamless integration of our method with mental health services and the creation of a friendly atmosphere. In our project,

The results of our project indicate the potential for a groundbreaking advancement in mental health support, where technology harmonizes with traditional care to offer comprehensive solutions. We foresee a future where our approach seamlessly integrates with mental health services, fostering a supportive environment that empowers individuals to manage their mental well-being effectively. Our project sets the stage for a more inclusive and promising future in mental health care, promoting accessibility and personalized support for a wide range of users.

REFERENCES

[1] Ajitha, P., Sivasangari, A., Immanuel Rajkumar, R., & Poonguzhali, S. (2021). Design of text sentiment analysis tool using feature extraction based on fusing machine learning algorithms. Journal of Intelligent & Fuzzy Systems, 40(4), 6375-6383.

[2] Zhou, D., Wang, Jianan, Zhang, Linhai, & He, Yulan. (2021). Implicit Sentiment Analysis with Event-centered Text Representation. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing.

[3] Mishra, Shreyash, Choubey, Siddhartha, Choubey, Abha, Yogeesh, N, Durga Prasad Rao, J, & William, P. (2022). Data Extraction Approach using Natural Language Processing for Sentiment Analysis. In 2022 International Conference on Automation, Computing and Renewable Systems (ICACRS).

[4] Banerjee, Tulika, Yagnik, Niraj, & Hegde, Anusha. (2021). Impact of cultural-shift on multimodal sentiment analysis. Journal of Intelligent & Fuzzy Systems, 41(5), 5487-5496.

[5] Nandwani, Pansy, & Verma, Rupali. (2021). A review on sentiment analysis and emotion detection from text. Social Network Analysis and Mining, 11(1).

[6] Tan, Kian Long, Lee, Chin Poo, Anbananthen, Kalaiarasi Sonai Muthu, & Lim, Kian Ming. (2022). RoBERTa-LSTM: A Hybrid Model for Sentiment Analysis With Transformer and Recurrent Neural Network. IEEE Access, 10, 21517-21525.

[7] Addepalli, Nishanth, Pabolu, Ravi Kanth, Ganesh Chennuru, Siva, & Vissampalli, Vara Lakshmi, & Madhumati, G L. (2023). Conversion of American Sign Language to Text Using Deep Learning for Feature Extraction and Naive Bayes for Classification. In 2023 IEEE 8th International Conference for Convergence in Technology (I2CT).

[8] Singh, Shailendra Kumar, & Sachan, Manoj Kumar. (2021). Classification of Code-Mixed Bilingual Phonetic Text Using Sentiment Analysis. International Journal on Semantic Web and Information Systems, 17(2), 59-78.

[9] Groh, Georg, & Hauffa, Jan. (2021). Characterizing Social Relations Via NLP-Based Sentiment Analysis. Proceedings of the International AAAI Conference on Web and Social Media, 5(1), 502-505.

[10] Zhang, Tong, Gong, Xinrong, & Chen, C. L. Philip. (2022). BMT-Net: Broad Multitask Transformer Network for Sentiment Analysis. IEEE Transactions on Cybernetics, 52(7), 6232-6243.

[11] Velampalli, Sirisha, Muniyappa, Chandrashekar, & Saxena, Ashutosh. (2022). Performance Evaluation of Sentiment Analysis on Text and Emoji Data Using End-to-End, Transfer Learning, Distributed and Explainable AI Models. Journal of Advances in Information Technology, 13(2).

[12] Abubakar, Amina Imam, Roko, Abubakar, Bui, Aminu Muhammad, & Saidu, Ibrahim. (2021). An Enhanced Feature Acquisition for Sentiment Analysis of English and Hausa Tweets. International Journal of Advanced Computer Science and Applications, 12(9).

[13] Barnes, Jeremy, Kurtz, Robin, Oepen, Stephan, Øvrelid, Lilja, & Velldal, Erik. (2021). Structured Sentiment Analysis as Dependency Graph Parsing. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers).

[14] Tesfagergish, Senait Gebremichael, Kapočiūtė-Dzikienė, Jurgita, & Damaševičius, Robertas. (2022). Zero-Shot Emotion Detection for Semi-Supervised Sentiment Analysis Using Sentence Transformers and Ensemble Learning. Applied Sciences, 12(17), 8662.

[15] Alexandridis, Georgios, Varlamis, Iraklis, Korovesis, Konstantinos, Caridakis, George, & Tsantilas, Panagiotis. (2021). A Survey on Sentiment Analysis and Opinion Mining in Greek Social Media. Information, 12(8), 331.