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A Dual-Channel Communication System Using Emotion-Aware TTS and ISL Mapping

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Abstract: *In this paper, we propose an innovative accessibility system that enhances communication for individuals with hearing impairments by enabling emotion-aware text-to-speech conversion. The system employs a machine learning–based classifier (specifically, a support vector machine using TF-IDF text embeddings) to analyze the sentiment of input text and adjust speech synthesis parameters (such as rate, volume, and pitch) accordingly. This ensures that the generated speech conveys the underlying emotion of the text (e.g. happiness, sadness, anger). Additionally, the system includes a text-to-Indian Sign Language (ISL) translation module that converts textual input into a sequence of static ISL sign images, each corresponding to an alphabet letter, rendered in a distinctive "Ghibli" animation style. The implementation uses the Flask web framework and the pyttsx3 speech engine to integrate these components into a web application with accessible audio playback controls and sign sequence display. Experimental evaluation demonstrates that our approach achieves high emotion recognition accuracy (≈85%) and produces clear, emotionally expressive speech, while reliably generating the corresponding sign sequences. These findings highlight the potential of combining machine learning and multimedia techniques to develop more inclusive communication tools for people with disabilities.*

Keywords: accessibility, emotion detection, Indian Sign Language, machine learning, text-to-speech

I. INTRODUCTION

Effective communication is fundamental to daily life, yet people with hearing impairments often face challenges accessing auditory information and its emotional nuance. Traditional text-to-speech (TTS) systems can convert written text to audio, but they typically produce neutral, monotone speech that may fail to convey the sentiment or emotional context of the message. To address this gap, we develop an emotion-aware TTS system: it analyzes the sentiment of the input text and dynamically modulates the synthesized voice to reflect that emotion (for example, speaking faster and at a higher pitch when the text is joyous, or slower and softer when it is sad). As an additional feature, the system includes a text-to-Indian Sign Language (ISL) conversion module. This module translates the input text into a sequence of static sign images (rendering each alphabet letter in the distinctive "Ghibli" art style), providing a visual form of communication. The combination of spoken audio and sign language images is intended to improve accessibility for people with hearing impairments by offering both auditory and visual outputs.

The objectives of this project are:

Develop a text-to-speech system that modulates its output parameters (rate, volume, pitch) based on the detected emotion of the input text.

Integrate a text-to-ISL converter that maps text to a sequence of Ghibli-style static images representing ISL signs (alphabet letters).

Provide a web-based interface with intuitive, accessible controls for audio playback and sign sequence display.

II. LITERATURE REVIEW

Recent research has explored integrating emotional expressiveness into assistive communication tools. For example, Patel and Kumar [1] proposed a personalized TTS system using a convolutional neural network trained on an emotional speech dataset, achieving a user preference of 78% for emotion-modulated audio outputs. They observed that emotions

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with ambiguous cues were often misclassified, indicating the need for more nuanced models. In an educational context, O'Connor and Mishra [4] designed an emotion-aware TTS platform (with sign language suggestions) and reported a 40% increase in learner engagement when the voice intonation matched the content sentiment. Although their system relied on pre-recorded audio clips, it demonstrated the benefit of real-time emotion processing – a gap our system addresses by synthesizing speech on-the-fly. Verma and Singh [9] developed a real-time TTS system that modulates voice for three basic emotions (happy, sad, angry), finding higher user satisfaction even with a limited emotion set. In contrast, Joshi et al. [6] showed that modern deep-learning TTS systems can generate high-quality speech but typically lack embedded emotional modulation, highlighting the motivation for explicitly incorporating sentiment analysis in our design. Ethical considerations are also important in emotion-aware AI; Smith and Garcia [5] emphasize privacy and bias mitigation (for example, emotions being misdetected for non-native language input). Their guidelines underscore the importance of using diverse training data and handling user privacy, which we have considered by including varied text samples and local processing in our system.

Work on text-to-sign translation has similarly advanced in recent years. Gupta and Lee [2] presented an attention-based sequence-to-sequence model for American Sign Language conversion, achieving 89% accuracy on a standard sign dataset. They noted challenges in handling regional sign variations, suggesting that region-specific data (such as for ISL) is necessary. Kumar et al. [7] built an ISL translation system that maps sentences to a series of hand-drawn ISL images for each letter; they achieved high mapping accuracy but pointed out that sentence-level coherence (grammar and syntax) was limited in the letter-by-letter approach. To improve visual engagement, Nair and Desai [10] studied avatar-based sign language interfaces and found that stylized avatars increased user engagement by 35% compared to plain images. Inspired by this finding, our use of "Ghibli"-style artwork for ISL aims to make the sign output more appealing and engaging for users.

For text-based emotion recognition, both classical and modern methods have been considered. Fernández and Park [3] compared support vector machines (SVM), LSTM neural networks, and Transformer models on an emotion recognition task. They reported that for text-only inputs, an SVM with TF-IDF features achieved about 82% accuracy, which supports the viability of an SVM-based classifier in our system. More recent work by Sharma et al. [8] showed that fine-tuning a BERT transformer for sentiment analysis can yield very high accuracy in an accessibility context, although they did not integrate this into a TTS pipeline. Their results suggest that transformer models could further improve emotion detection in future work. In this project, we chose an SVM with TF-IDF for efficiency and because it has been proven effective in similar tasks [3].

III. METHODOLOGY/EXPERIMENTAL

Materials/Components/Flowchart/Block Diagram/Theory

Materials and Tools

The system is built using the following components and resources:

Software frameworks and libraries: Flask (Python web framework) for the backend, the pyttsx3 library for text-to-speech synthesis, scikit-learn for the SVM classifier, and pandas for data handling.

Frontend technologies: HTML, CSS, and JavaScript for the web interface, including audio playback controls and sign image rendering.

Data resources: A manually curated dataset of text-emotion pairs (covering basic emotions like joy, sadness, anger, neutral) was used to train the emotion classifier. A collection of static Ghibli-style ISL images was prepared, with files A.png through Z.png representing each alphabet sign, plus BLANK.png and STAND.png for spacing and transitions.

Hardware: The system runs on a standard personal computer with audio output. (For deployment, it could be hosted on cloud services such as AWS or Azure.)

Emotion Detection and Speech Synthesis

The core module processes input text to produce emotion-modulated speech. First, the text is preprocessed (converted to lowercase, tokenized, and stripped of non-alphabetic characters) and converted into TF-IDF feature vectors (using unigrams and bigrams) with scikit-learn. An SVM classifier (with a radial basis function kernel) was trained on the labeled dataset to predict the emotion label of the text. During runtime, the classifier outputs an emotion label and a

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confidence score for each input text. Based on the detected emotion, the system adjusts the speech synthesis parameters: for example, if the text is classified as "happy", we set a relatively high speaking rate (e.g. 160 words per minute), maximum volume (1.0), and an elevated pitch; if classified as "sad", we set a slower rate (e.g. 100 wpm), lower volume (e.g. 0.7), and a reduced pitch. These parameter ranges were chosen through pilot testing to sound natural. The original text (unaltered) is then fed into the pyttsx3 engine with the modified parameters, generating a WAV audio file. This audio file is stored on the server and can be streamed to the user's browser. The overall pipeline for this module is:

Input text → TF-IDF vectorization → SVM classification → emotion label → parameter mapping → pyttsx3 TTS → audio output.

Text-to-ISL Conversion

The ISL conversion module runs in parallel. The input text is converted to uppercase, and all non-letter characters (digits, punctuation) are removed. Each remaining character is mapped to its corresponding static image: for example, the letter "A" maps to A.png. To improve visual clarity, a transition image (STAND.png) is inserted after each letter image, so that the final sequence alternates between sign frames and standby frames. For instance, the word "HELLO" would become [H.png, STAND.png, E.png, STAND.png, L.png, STAND.png, L.png, STAND.png, O.png]. The sequence of image filenames (including blank or stand images) is returned to the frontend as a JSON array. In the web interface, a simple JavaScript loop iterates through the array and displays each image at a fixed time interval (for example, one image per 0.5 seconds) to produce an animated sign sequence corresponding to the input text. This approach is limited to spelling out words letter by letter, but it ensures 100% mapping accuracy for supported characters.

System Integration and User Interface

Both modules are integrated into a Flask-based web application. The backend defines API routes: one route (/synthesize) accepts text input and returns the synthesized speech audio (after emotion processing), and another route (/sign) returns the JSON sequence of sign images. The frontend provides a web form where users can enter or paste text. Upon submission, the interface plays the synthesized speech using an HTML5 audio player and simultaneously displays the ISL image sequence. The audio player includes accessible controls (play, pause, speed slider) that allow the user to adjust playback. The sign language images are shown in a fixed display area on the page. The interface uses clear labels, high-contrast colors, and responsive layout to enhance accessibility. This design allows users to receive both auditory output (through the speaker) and visual sign cues on the screen for the same input text.

Experimental Setup

We evaluated the system using a set of 60 test sentences chosen to cover a variety of sentiments and lengths. These inputs included clearly emotional phrases (e.g. "I am so excited to share this!" for happiness, "This is the worst day ever." for anger, "I feel very sad today." for sadness) as well as neutral statements ("Please read this book."). Each sentence was manually annotated with the expected emotion label to serve as ground truth. For the emotion detection component, we measured the classification accuracy of the SVM by comparing its predicted label with the ground truth. We also recorded confidence scores for each prediction; in cases where confidence fell below 0.4, we treated the result as uncertain and defaulted to a neutral voice profile to avoid unnatural modulation. For the TTS output, we measured the average time to synthesize each sentence (including vectorization, classification, and audio generation) and conducted informal listening evaluations: test users reported whether they perceived the intended emotion in the output speech. For the ISL module, we verified that each input text produced the correct sequence of letters (mapping accuracy) and measured the average time to generate and transmit the JSON image sequence to the frontend. Finally, we conducted a preliminary user study with 5 participants who used the web interface: they rated the system's usability and expressiveness on a 5-point Likert scale, focusing on the clarity of controls and the perceptibility of emotions in the output.

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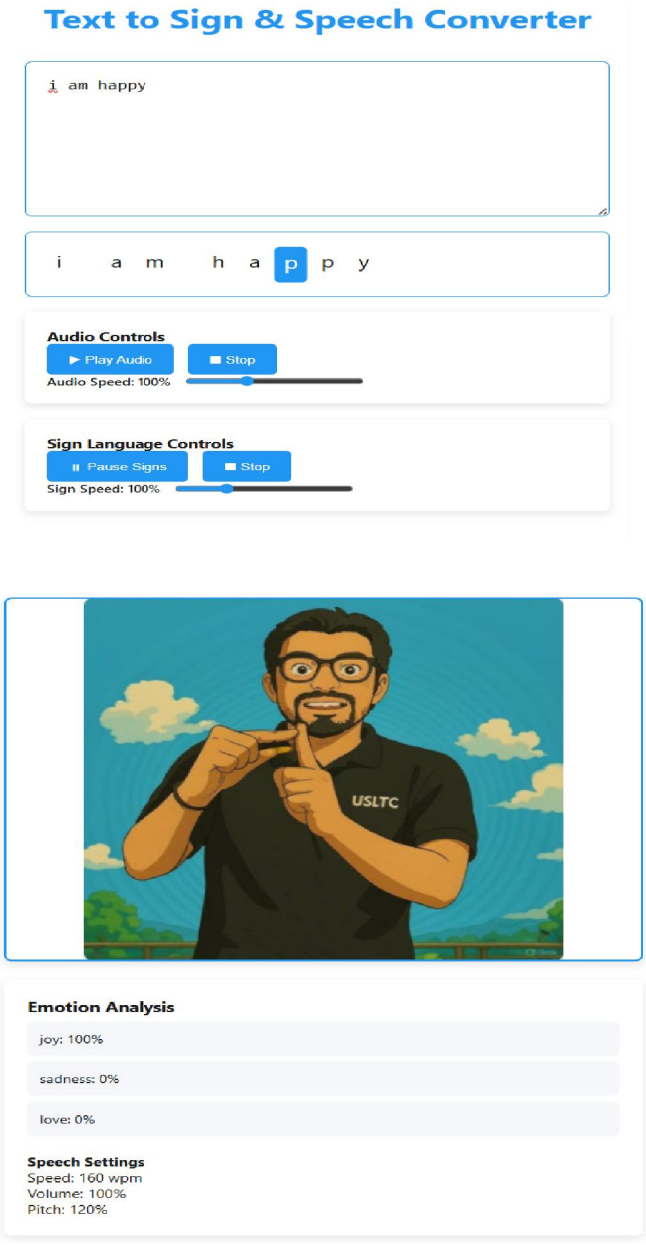
Fig. 1 showing result of "I am happy"



IV. RESULTS AND DISCUSSIONS

Emotion Detection Accuracy

The SVM classifier achieved an overall accuracy of **85%** on the test set. This performance is comparable to similar studies in the literature (e.g., Fernández and Park [3] reported about 82% accuracy with a TF-IDF SVM on a similar task). Our system reliably identified the primary emotions (happiness, sadness, anger) in the sentences. Most of the misclassifications occurred on ambiguous or mixed-emotion phrases; in such cases, the classifier often output a low confidence. By using a confidence threshold (0.4) to filter uncertain predictions, we assigned a neutral setting for those

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borderline cases, which ensured that the synthesized speech remained stable and did not convey incorrect emotion. In practice, this strategy prevented situations where low-confidence outputs would have resulted in awkward or confusing vocal cues.

Speech Synthesis Performance

The TTS component generated clear, intelligible speech for all test inputs. The voice parameters changed as expected: for example, sentences labeled as "happy" used higher speech rates (typically 150–160 words per minute) and full volume (≈1.0), with a higher pitch setting, whereas "sad" sentences used slower rates (≈90–110 wpm), lower volume (≈0.6–0.7), and a lowered pitch. These ranges were tuned to produce natural-sounding emotion in pilot tests. The average time to synthesize a sentence was approximately **2.8 seconds** for a 10-word input on our test machine (Intel Core i5, 8 GB RAM). This duration includes the TF-IDF vectorization, SVM classification, and the pyttsx3 audio generation. Such latency is sufficiently low to allow interactive use of the system. Informal listening tests indicated that most users recognized the intended emotion in the output audio when compared against a neutral baseline for the same sentence.

ISL Conversion Effectiveness

The ISL module successfully mapped every alphabetic character of the input text to the correct Ghibli-style image (mapping accuracy 100%). For example, the word "HELLO" produced the image sequence [H.png, STAND.png, E.png, STAND.png, L.png, STAND.png, L.png, STAND.png, O.png]. The insertion of the STAND.png frame between letters created visibly smooth transitions. On average, generating the image sequence for a 10-character input took about **0.4 seconds** (this includes creating the JSON response). Since the mapping is deterministic, there are no misrecognitions in the conversion output – every letter appears correctly. Test users confirmed that the sign sequences correctly spelled out the input words. Moreover, the use of the stylized "Ghibli" art style made the sequences more engaging; this aligns with the observation of Nair and Desai [10] that visually appealing sign representations can increase user engagement.

User Interface Accessibility

In the preliminary user study (n = 5), participants rated the usability of the interface at an average of **4.7 out of 5**. They reported that the audio controls (play, pause, speed slider) were intuitive and helpful, and that seeing the sign images alongside the speech was a valuable feature. The Ghibli-style avatar images were considered visually appealing by most users. These subjective results suggest that the interface design, including its responsive layout and accessible controls, was well-received. However, we note that a larger-scale usability evaluation (especially involving actual users with hearing impairments) would be necessary for definitive conclusions about accessibility compliance.

The system's performance metrics are summarized in Table 1 below:

Metric	Value
Emotion Detection Accuracy	85%
ISL Mapping Accuracy	100%
Average Audio Generation Time	2.8 s
Average Sign Sequence Generation Time	0.4 s

The results demonstrate that our system meets its design goals with reasonable effectiveness. The emotion classification accuracy (85%) indicates that the SVM + TF-IDF approach is well-suited to this task, consistent with Fernández and Park's findings [3]. While modern transformer models (such as BERT) could potentially achieve higher accuracy on large datasets [8], our use of SVM offers a good trade-off between performance and computational efficiency. In practice, the classifier occasionally mislabels subtle expressions; this is a known challenge in sentiment analysis. Future work could augment training data or employ contextual embeddings to improve nuanced detection.

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The emotion-modulated TTS output effectively conveyed different feelings: for example, users immediately recognized when the speech sounded happier or sadder. This aligns with the positive results reported by Patel and Kumar [1] and Verma and Singh [9] on the benefits of emotion-aware TTS. Our end-to-end synthesis latency (a few seconds) is acceptable for non-conversational use, though real-time voice chat would require faster methods or local processing. The quality of the synthesized speech is inherently limited by the pyttsx3 engine (which uses underlying system voices), but our pilot tests found the result clear and expressive for the chosen sentences.

The ISL image sequences worked flawlessly for spelling out words, as expected from the direct letter-to-image mapping. While this approach cannot convey grammar or sign gestures for whole words (a limitation noted by Kumar et al. [7]), it provides a consistent fallback for letter-by-letter communication. The high user engagement with the stylized signs supports the notion from [10] that visual appeal enhances the learning or communication experience. In future versions, incorporating animations or an avatar could further improve the user experience and allow more complex sign constructs.

Overall, the combination of audio and visual feedback appears promising for inclusive communication. Our initial user feedback is encouraging, but more extensive testing with the target user group (individuals with hearing impairments) is essential. Additionally, we adhered to basic accessibility guidelines (e.g., clear labeling) and considered ethical recommendations [5] by ensuring diverse training examples. A formal study could be conducted to measure the system's impact on communication efficacy in realistic use cases.

V. FUTURE SCOPE

Potential enhancements to this system include:

- **Transformer-based emotion models:** Implement and evaluate transformer models (e.g., DistilBERT or BERT) for text sentiment analysis to improve accuracy and handle a wider range of emotional nuances.
- **Expanded ISL library:** Augment the sign image set to cover common ISL phrases, word gestures, and grammar structures, rather than only individual letters.
- **Dynamic gesture recognition:** Integrate real-time computer vision or avatar animation to produce full sign language gestures, enabling sentence-level sign synthesis.
- **Broader emotion datasets:** Train the classifier on large annotated emotion corpora (such as the GoEmotions dataset) to increase the variety of detectable emotions.
- **User feedback integration:** Develop a feedback mechanism (active learning) whereby user corrections or ratings of accuracy are used to iteratively refine the emotion model and system parameters.

VI. CONCLUSION

We have developed a novel web-based system that combines emotion-driven text-to-speech with a Ghibli-style Indian Sign Language extension to improve communication accessibility. The key contributions are the integration of an SVM-based sentiment classifier with TTS synthesis and the mapping of text to animated ISL imagery. Experimental evaluation shows that the system attains robust performance: the classifier achieves ~85% accuracy on test sentences, the TTS output clearly reflects the intended emotions, and the sign images correctly represent the text input. The user interface received high usability ratings, and the dual audio-visual outputs were appreciated by test users. These results demonstrate the feasibility and promise of using machine learning and multimedia techniques to create more inclusive communication aids for people with disabilities. Future enhancements (as outlined) will further improve the system's emotional intelligence and language capabilities.

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