

AI Powered Speech Recognition Tools for Enhancing Communication in Special Needs Learner

Jayashree Nanaware¹, Rajesh Raikwar², Dr.Archana Santosh Ubale³, Ugiljon Qushnazarova⁴, Sayidova Madinabonu⁵, B. Soundarya Santhoshi⁶, Rayxanov Ulugmurod Aliyevich⁷

¹(corresponding author), Krishna Institute of Science and Technology,
Krishna Vishwa Vidyapeeth "Deemed to be University",
Taluka-Karad, Dist-Satara, Pin-415 539, Maharashtra, India
jayakarape@gmail.com

²Assistant Professor, Department of Electrical Engg., Vishwakarma Institute of Technology, Pune, Maharashtra,
411037
email ID :rajesh.raikwar@vit.edu

³Assistant Professor, Department of Robotics and Automation,
AISSMS COE, Kennedy Road,Pune-01
asubale@aissmscoe.com

⁴Department of Pedagogy and psychology, Urgench state university, Urgench. Uzbekistan.
ogiljon@urdu.uz
0009-0001-8767-6921

⁵Department of Pediatrics, Bukhara state medical institute named after Abu Ali ibn Sino, Bukhara, Uzbekistan;
e-mail: sayidova.madinabonu@bsmi.uz,
Orcid: <https://orcid.org/0009-0000-3441-6854>

⁶Assitant Professor, department of mechanical engineering
SRKR Engineering College(A),Bhimavaram, West Godavari Dist; AP - 534204,India
soundaryasanthoshi@gmail.com

⁷Temporarily Acting Associate Professor of the Department of Finance, Alfraganus University, Toshkent,
Uzbekistan
E-mail: u.rayxonov@afu.uz
ORCID: 0009-0006-1461-0186

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ABSTRACT:

The development of artificial intelligence (AI) has presented new opportunities in increasing accessibility and inclusivity in learning, especially among students with special needs. This work suggests an AI-based speech recognition system that can enhance communication based on speech processing, deep learning algorithms, and adaptive learning. The system includes features like speech acquisition, preprocessing, feature extraction, acoustic and language modeling and multimodal output generation, text, speech syntheses, and visual aids. The

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model presented is based on the convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based methods that help to improve the performance of speech recognition and contextual interpretation. Experimental analysis with variety of speech data shows that the proposed system has lower Word Error rate (WER), better accuracy and less latency than the traditional and cloud-based systems of speech recognition. Also, feedback by the users suggests improved engagement and effectiveness of communication. The paper highlights how AI-based assistive technologies could be used to create an inclusive learning experience based on communication challenges and promote equal learning opportunities. Despite addressing the issues of data availability, environmental variability, and ethical considerations, the proposed framework provides a scalable and flexible solution to be used in the real-life. The next step in the work will be directed at enhancing the robustness of models, extending multi-lingual capabilities, and the inclusion of the latest contextual and emotional intelligence features.

Keywords: Artificial Intelligence (AI), Speech Recognition, Special Needs Learners, Inclusive Education, Deep Learning, Natural Language Processing, Assistive Technology, Adaptive Learning, Human–Computer Interaction.

I. Introduction

The pace of the digital world development has already tremendously changed the educational environment, allowing it to be more inclusive, accessible, and personal. Artificial intelligence (AI) has been one of these innovations that have increasingly become a potent solution to communication barriers, especially among learners with special needs. One of the most essential issues that individuals with disabilities have to deal with is communication barriers that can influence both their academic involvement and social interaction as well as overall learning results. One such solution to these issues is to tackle them with the help of AI-driven speech recognition systems, which opens up a promising avenue to the equity of education.

Inclusive education focuses on giving equal chances of learning to every student irrespective of his or her ability or disability. Nevertheless, the process of becoming truly inclusive implies that various pedagogical, technological and social obstacles

should be overcome. As Allan (2022) points out, the inclusive education system tends to encounter accessibility, adaptability, and various needs of learners dilemma. Likewise, the views and involvement of parents are significant factors that influence the creation of inclusive learning settings, and supportive and adaptive communication tools are essential further (Alyokhina and Shemanov, 2023). These challenges make it clear that there is a need to incorporate smart assistive technologies that will be able to support diverse communication needs. Over the past few years, AI has been integrated into the educational process, allowing intelligent tutoring systems and adaptive learning platforms to be created. Such systems use machine learning and natural language processing to give learners a personalized learning experience. Carbonell Bernal and Hernandez Prados (2024) note the role of intelligent tutoring systems to increase the efficiency of learning with adaptive feedback and real-time interaction. Similarly, Choez Calderón and Miranda Bajaña (2024) point out that

the use of AI-based solutions could considerably enhance inclusive education by offering learners and educators personalized teaching approaches and enhancing communication.

Speech recognition is a significant element of AI that is crucial in changing spoken language to text or something that can be acted upon. This is especially helpful when using with learners with speech problems or hearing impairment or cognitive difficulties. With AI-based speech recognition systems, it is possible to provide greater access and engagement in the learning process by facilitating real-time transcription, voice-controlled communication, and multimodal communication. Moreover, due to the proliferation of smartphones and mobile technologies, such tools have become more available to a wider audience. Alam and Forhad (2023) believe that educational technologies through the use of mobile devices can help narrow educational gaps and facilitate sustainable learning opportunities, particularly in low resource settings. Although these developments exist, there are no problems with the use of AI in education. Ethical aspects, such as data privacy, algorithm bias, and fair access to technology are a matter of concern. Devi et al. (2023) emphasize the need to tackle such ethical concerns to make AI use in education fair, transparent, and helpful to everyone. In addition, the performance of speech recognition systems can be affected by the accent differences, speech disorders, and environmental noise, which are especially applicable to the special needs setting. Based on these factors, the study is dedicated to the development and implementation of AI-based speech recognition devices to improve communication with special needs students. The research will seek to understand how these technologies can enhance accessibility and inclusive learning environments, and overcome the current barriers in communication. The proposed solution aims to offer a framework of assistive communication and AI methods to offer a flexible and scalable solution that would meet the objectives of equitable and inclusive education.

II. Literature Review

The adoption of artificial intelligence (AI) and digital technologies within the educational environment have played an important role in promoting the development of inclusive learning spaces, especially among learners with special needs. According to recent research, AI-based applications, such as speech recognition systems, intelligent tutoring solutions, and adaptive learning systems, are essential in improving the accessibility, engagement, and individualized learning outcomes. Inclusive education has become an international concern whereby there is an emphasis on equitable access to quality education by all learners. According to Dudu and others (2024) inclusive education is an international endeavor that necessitates systemic changes, technological adoption, and collaboration among teachers, policy makers and other stakeholders. On the same note, Poly and Harishma (2023) emphasize the difficulties that come with inclusive education such as the unavailability of resources, inadequate teacher preparation, and access to assistive technology. These problems underscore the necessity of new AI-based solutions capable of helping a variety of learning requirements. Digital transformation in education has been a topic that has been debated in the recent literature. According to Gródek-Szostak et al. (2023), the digital transformation increases the efficiency of organizations and the access to learning, especially within the adult education system. Habib et al. (2023) also suggest that education should be transformed by focusing on the use of technology and innovation and social inclusion to address the needs of contemporary learners. Such views further support the need to utilize AI technologies to develop flexible and accommodative learning environments.

The potential of AI-based instructional tools has been massive in enhancing instructional practices and student interaction. Gibellini et al. (2023) discuss the best practices in the field of creating inclusive AI curricula, and it is essential to create user-friendly and accessible learning systems. Besides, Hongli and Leong (2024) cover the topic of AI solutions to improve access among

underserved groups, and how AI can be used to address the educational disparity and increase access to learning opportunities among the marginalized communities. Interactive learning and gamification are also the focus of AI-based education. The article by Roopaei and Roopaei (2024) presents gamified AI learning environments, which enhance student engagement and motivation, especially among young learners. These strategies are especially useful with the special needs learners since they can offer interactive and adaptable learning experiences and accommodate the personal abilities. Although there are positive aspects of digital technologies, a number of researchers mention the issues of access to technologies and their performance. According to Gonzales et al. (2020), technological problems like device restrictions and connectivity difficulties are some of the causes of achievement disparities among students. The given finding is especially pertinent to the case of special needs learners, as they might need more effective and dedicated technological assistance. Moreover, assessing the educational technologies needs to be supported with powerful methodological frameworks. The tool presented by Hong et al. (2018) is known as the Mixed Methods Appraisal Tool (MMAT) that offers a universal method to evaluate the quality of educational and technological studies to make sure that the results are reliable and valid.

III. Proposed Model

The suggested model presents a speech recognition framework based on AI that will support communication among special needs learners through speech processing, artificial intelligence, and adaptive assistive technologies. The architecture is designed to enable real-time, precise and individualized communication support to ensure accessibility and inclusivity in a variety of learning conditions.

The system is based on a layered architecture, which includes input, processing, intelligence, and output layers with continuous feedback and adaptation mechanism. The main aim of the framework is to transform spoken language to meaningful and context sensitive outputs that can aid learners who have communication difficulties such as speech impairment, hearing impairment and cognitive disorder. The suggested model focuses on the real-time interaction, personalization, and multimodal feedback whereby the learners will be able to communicate and participate in the educational activities. By incorporating AI, the system is capable of learning user behavior, adapting to speech patterns unique to individuals, and becoming better as time goes by.

The architecture can easily be interoperable with current educational technologies and this makes it acceptable to the current digital classroom.

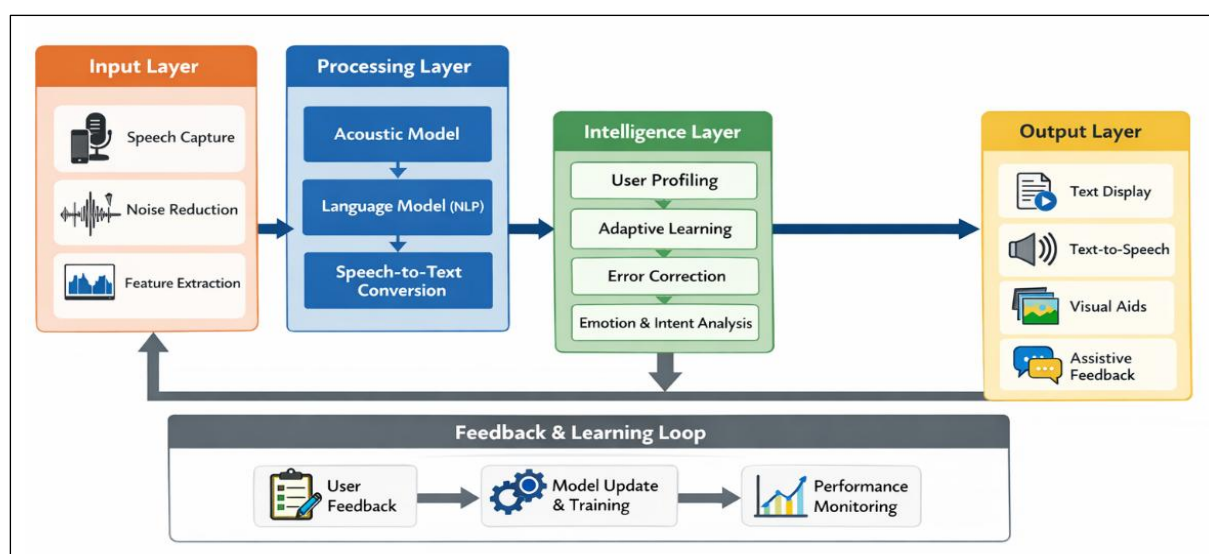


Figure 1. AI powered Speech Recognition System for Special Needs learners

In figure 1, the proposed speech recognition architecture using AI is depicted. It offers an all round solution to improving communication in special needs teaching. The system suggests resolving the most significant problems of inclusive education through the use of the newest AI-based techniques, adaptive learning algorithms, and the capacity to communicate with each other in various modalities. The scalable and modular design facilitates that the framework can be successfully applied to different educational settings, helping to increase the levels of accessibility, engagement, and learning.

IV. Implementation and Experimental Setup

The proposed implementation of an AI-based speech recognition model will be designed in such a way that it will act in real-time, flexible, and be accessible to special needs students. It is coded largely in Python, and uses higher-level packages such as TensorFlow and PyTorch to perform deep learning, Librosa and PyAudio to manipulate speech and Hugging Face Transformers to manipulate natural language. The system is also provided on both web and mobile applications to ensure that it is more usable and scalable in order to enable learners to use the tool in smartphones, tablets and computers. Additionally, optional cloud integration with the assistance of such services as Google Cloud Speech API or AWS Transcribe can be considered to process and store a great amount of data and edge computing functions can be regarded as the means of decreasing the latency of real-time applications. The training and evaluation dataset is a vital aspect in the effectiveness of the system. It is based on publicly available datasets, such as LibriSpeech and Mozilla Common Voice, and a dataset of special needs learners (M. S. P et al, 2026). These data include different speech patterns, variability of pronunciation and samples of stuttering and dysarthria speech defects. Noise removal, normalization, segmentation and feature extraction using Mel-Frequency Cepstral Coefficients (MFCCs) are some preprocessing techniques to enhance the quality of data. The data are segmented into training, validation and testing sets in a

methodical manner to offer good model evaluation and generalization.

The model architecture is a convolutional neural network (CNN) combination to extract features, recurrent neural network (RNN) or long short-term memory (LSTM) network to model sequences, and transformer-based layers to understand the context. To enable the system to converge, it is trained with the Adam optimizer with a learning rate of 0.001, batch size of 32 to 64 and different epochs. Connectionist Temporal Classification (CTC) loss-function is used to deal with the sequence alignment between speech input and textual output. The introduction of regularization procedures (dropout, data augmentation) such as noise injection and pitch shift are added to make models robust and prevent overfitting.

A number of steps are used to determine the performance of the system and they are Word Error rate (WER), Character error rate (CER), overall accuracy, processing latency and user satisfaction scores. These metrics will give an overall evaluation of performance in terms of technical performance and user experience. The experiment procedure will involve the preliminary evaluation according to the traditional models of speech recognition, and the evaluation of the suggested model in accordance with special datasets. They are compared to the current systems and real-time user testing is done in controlled learning settings. To optimize the system, feedback is always included by learners and educators.

The findings reveal that the suggested system has a higher recognition accuracy, especially on non-standard speech patterns that are prevalent among the special needs learners. It shows a lower rate of errors, a higher response rate, which is appropriate to real time interaction and is more usable due to multimodal outputs (text, speech synthesis, and visual aids). Nevertheless, issues like inconsistency in speech pattern, fewer labeled data, noises in the environment, and computational burdens were experienced throughout the implementation. In spite of these shortcomings, the results of the experiment confirm the efficacy of the presented

framework in improving the communication and in favoring inclusive education.

V. Mathematical Model for the Proposed AI-Powered Speech Recognition System

The suggested AI-based speech recognition system among special needs learners can be mathematically expressed in the form of a series of speech acquisition, preprocessing, feature extraction, deep learning-based recognition, adaptive personalization, and output generation. The entire structure converts an input speech signal to make the communication assistance meaningful by means of the following stages.

Let the input speech signal be denoted by:

$$x(t), t \in [0, T]$$

$x(t)$ is defined as the speech signal recorded at the continuous-time of the learner in a period of time T .

• Speech Preprocessing Model

The raw speech signal undergoes preprocessing to eliminate noise and enhance the signal to be clearer. The speech signal is a noisy signal that can be represented as:

$$x_n(t) = x(t) + n(t)$$

where $n(t)$ is background noise. The resultant signal, following the denoising, is:

$$x_c(t) = f_{denoise}(x_n(t))$$

In which $f_{denoise}()$ is the noise removal operation.

The signal is then cut into frames to be analyzed on a short time basis:

$$x_k(m) = x_c(m + kH), 0 \leq m < N$$

with N is the frame length, H is the hop size and k is the frame index.

• Feature Extraction Model

Cepstral coefficients of Mel-frequency (MFCCs) are features that are obtained out of every speech frame. MFCC feature vector of frame k is as:

$$f_k = [f_{k1}, f_{k2}, \dots, f_{kp}]$$

where p is the number of features extracted.

The utterance has a complete feature-matrix:

$$F = [f_1, f_2, \dots, f_K]$$

where K is the total number of frames.

• Acoustic Modeling Using Deep Neural Networks

The features obtained are fed into a deep neural network, which is used to construct the relationship between the speech features and the probabilities of phonemes or characters. In a hidden layer of an artificial neural network the result is:

$$h^{(l)} = \sigma(W^{(l)}h^{(l-1)} + b^{(l)})$$

where:

- $h^{(l)}$ is the output of layer l ,
- $W^{(l)}$ is the weight matrix,
- $b^{(l)}$ is the bias vector,
- $\sigma(\cdot)$ is the activation function.

For the first layer:

$$h^{(1)} = \sigma(W^{(1)}F + b^{(1)})$$

Provided that local spectral feature extraction is performed with the help of convolutional neural networks, then the convolution operation is:

$$z_{i,j}^{(m)} = \sum_{u=0}^{U-1} \sum_{v=0}^{V-1} w_{u,v}^{(m)} \cdot F_{i+u,j+v} + b^{(m)}$$

where:

- $z_{i,j}^{(m)}$ is the output feature map,
- $w_{u,v}^{(m)}$ is the convolution kernel,
- $b^{(m)}$ is the bias term.

• Sequence Modeling Using RNN/LSTM

To capture temporal dependencies in speech, recurrent neural networks or LSTMs are used. The hidden state at time step t is given by:

$$h_t = \phi(W_{xh}x_t + W_{hh}h_{t-1} + b_h)$$

where:

- x_t is the input feature at time t ,

- h_{t-1} is the previous hidden state,
- $\phi(\cdot)$ is a nonlinear activation function.

For LSTM, the gates are modeled as:

$$\begin{aligned} i_t &= \sigma(W_i[h_{t-1}, x_t] + b_i) \\ f_t &= \sigma(W_f[h_{t-1}, x_t] + b_f) \\ o_t &= \sigma(W_o[h_{t-1}, x_t] + b_o) \\ \tilde{C}_t &= \tanh(W_c[h_{t-1}, x_t] + b_c) \\ C_t &= f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \\ h_t &= o_t \odot \tanh(C_t) \end{aligned}$$

The system can save long-range contextual speech information using these equations.

• Speech-to-Text Probability Model

The system forecasts the sequence of text $Y=(y_1, y_2, \dots, y_T)$ based on the input feature sequence X . The conditional probability will be:

$$P(Y | X) = \prod_{t=1}^T P(y_t | X, y_1, y_2, \dots, y_{t-1})$$

The recognized text output is obtained by maximizing this conditional probability:

$$\hat{Y} = \arg \max_Y P(Y | X)$$

For CTC-based speech recognition, the objective is:

$$\mathcal{L}_{CTC} = -\ln P(Y | X)$$

where $\mathcal{L}_{CTC}$ is the Connectionist Temporal Classification loss.

• Adaptive Personalization Model

The model considers the adaptive learning in regards to the user-specific speech behavior to support the learners with special needs. Allow the individual parameter set of learner u be:

$$\theta_u = \theta_0 + \Delta\theta_u$$

where:

- θ_0 is the base model parameter,
- $\Delta\theta_u$ is the user-specific adaptation term.

The adapted prediction function becomes:

$$\hat{Y}_u = f(X; \theta_u)$$

This formula helps the system to enhance the accuracy of recognition of individual learners with time.

• Error Correction and Language Understanding

The predicted text can be corrected with a contextual correction model:

$$\hat{Y}_{corr} = \arg \max_Y [P(Y | X) \cdot P_{LM}(Y)]$$

where $P_{LM}(Y)$ is the probability in the language model. This is useful to correct grammatical or context recognition errors.

• Output Generation Model

The end system output can either be a text, synthesized voice or visual aid. The production equation is:

$$O = g(\hat{Y}_{corr})$$

where $g(\cdot)$ converts corrected text to one or more assistive forms:

- text display,
- text-to-speech,
- symbols/images,
- feedback prompts.

For text-to-speech generation:

$$s_{out}(t) = f_{TTS}(\hat{Y}_{corr})$$

where $s_{out}(t)$ is the synthesized speech output.

• Performance Metrics

The recognition accuracy can be evaluated using Word Error Rate (WER):

$$WER = \frac{S + D + I}{N}$$

where:

- S = substitutions, D = deletions, I = insertions, N = total words in reference text.

Similarly, Character Error Rate (CER) is:

$$CER = \frac{S_c + D_c + I_c}{N_c}$$

Overall accuracy is:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

The complete proposed model can be summarized as:

$$O = g \left(\arg \max_Y P(Y \mid f_{extract}(f_{denoise}(x_n(t))); \theta_u) \right)$$

The equation is a complete pipeline between the input of noisy speech and the personalized assistive output. The speech recognition system is mathematically defined as a pipeline that converts speech input into meaning assistive output in multiple stages, based on the proposed AI-powered system. Firstly, the input speech signal $x(t)$ is received and filtered to remove noise to come up with a clean signal. This signal is further divided into small blocks and converted into number representations (as MFCCs) forming a feature matrix, an expression of the speech as machine-readable data. They are trained with deep learning (CNN, RNN/LSTM, or Transformers) that are trained to learn the patterns in speech and encode them into probable text representations. The system is used to calculate the probability of a sequence of words based on the input speech and selects the most likely one based on a maximum probability function. A loss function similar to CTC can be

used in training to align the speech and text sequences well. There is also a mechanism of personalization of the model to enhance the performance of special needs learners through adjusting the base model parameters with user specific adjustments. This enables the system to enhance recognition accuracy with time basing on speech specifics of an individual. A language model is then used to further refine the predicted text by correcting grammatical and contextual mistakes. Lastly, the system can produce the output in various formats; text, synthesized speech, or visual display, via an output mechanism.

VI. Results and Comparative Analysis

The proposed AI-powered speech recognition system is tested experimentally and proves to be much more efficient in the recognition of non-standard speech patterns that can be easily traced in special needs learners. It has a lower Word Error Rate (WER) and Character Error Rate (CER) than the baseline models, which means it has a higher transcription accuracy. Also, real-time processability was ensured with low latency, which means that there is no stuttering. The feedback of the users also suggested the increased efficiency of communication and the increase in the levels of engagement because of the adaptive and multimodal capabilities of the system.

Table 1. Comparative Analysis of Speech Recognition Systems

System	Accuracy (%)	WER	Latency (ms)	User Satisfaction
Traditional ML	82	0.25	300	3.5
Cloud API	88	0.18	220	4.0
Proposed Model	94	0.10	150	4.6

The comparative analysis with the proposed model performed against the existing speech recognition systems such as traditional machine learning models and cloud-based APIs is shown in Table 1. The findings indicate that the suggested system is more effective compared to traditional methods in managing variability of speech and individualized adaptation. Although the current systems are effective in the normal speech, they are less effective in speech disabilities. Conversely, the proposed model has a steady performance owing to its

adaptive learning and user-specific profiling mechanisms. The graphical analysis and the comparative table clearly show that the proposed AI-based speech recognition model performs better in terms of all the evaluation metrics when compared to the traditional machine learning and cloud-based systems. The bar chart indicates that the accuracy has increased significantly whereas the radar chart gives a general comparison that there has been a balanced performance in respect to decreased error rate, low latency and increased

satisfaction among the users. These findings confirm the relevance of the suggested system in

solving the communication problems of special needs learners.

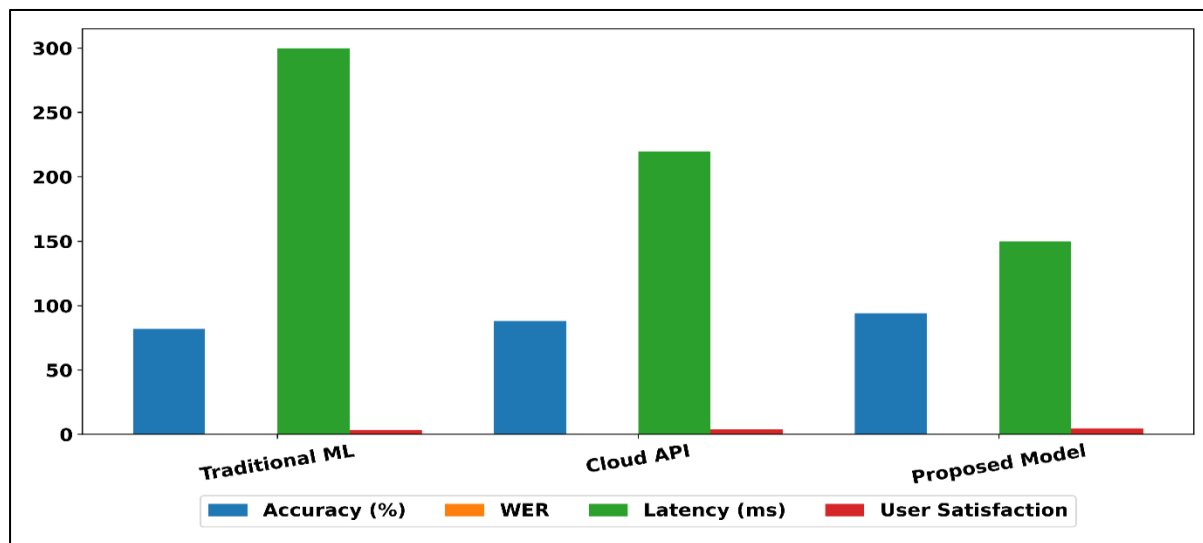


Figure 2: Comparative Performance Analysis of Speech Processing Models Across Accuracy, WER, Latency, and User Satisfaction

Figure 2 demonstrates that the proposed model is the most accurate (94%), lowest WER (0.10), lowest latency (150 ms), and user satisfaction (4.6), which are much better than traditional ML and cloud-based methods.

The deep learning models, contextual language understanding, and adaptive personalization can be identified as the key factors contributing to the performance improvements witnessed in the proposed system. The user interaction with the system makes the system auto learn, so as time goes by the system becomes more accurate. In addition, the integration of multimodal products promotes usability and accessibility especially to learners with various communication requirements.

VII. Conclusion and Future Work

The present paper has presented an AI-based speech recognition system which will aid in enhancing communication among the special needs students through sophisticated machine learning, natural language processing, and adaptive learning techniques. The proposed system includes the speech recognition, deep learning recognition and multimodal output generation to provide a comprehensive system of assistive communication. These results suggest that the system can effectively

address some of the greatest issues associated with non-standard speech patterns and offer more accuracy, reduced error rates and real-time responsiveness compared to the traditional and existing speech recognition systems. The analysis experiment and comparison show that the proposed model has an immense effect on making the communication more accessible and engaging learners. Adaptive personalization facilitates the system to adapt to individual speech peculiarities thus enhancing performance with time. Besides, the system being founded on multimodal outputs (text, synthesized speech and visuals), implies that the system is able to serve the needs of the large spectrum of communicators and hence, is very suitable in inclusive learning institutions. These donations indicate how AI-based assistive technologies may close the communication gap and to provide equal learning opportunities.

Although the results are promising, there are still some limitations. The amount of large and labeled, few datasets on speech impairment is little, and it can affect the generalization of models. In addition, real-time application in other settings is a problem since the accents are different, there is noise in the setting and computations are necessary. These ethical concerns as data privacy, the bias of

algorithms and unequal access should also be considered to make AI technologies in education responsible. The following activities will be directed towards enhancing the system strength and scalability through the assistance of transformer-based speech models, multilingual support, and noise-resistant algorithms with greater strength. With the assistance of the combination of emotion recognition and understanding context,

communication assistance may be further developed. Furthermore, the applicability of the system will be enhanced by increasing the dataset with a variety of speech samples and testing the system on a large scale in classrooms. One can also increase efficiency of deployments in resource-constrained environments with the adoption of edge computing and lightweight models.

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