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Development Approach Towards English Speech To Marathi Speech Language Translation

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Abstract: *The increasing demand for real-time language translation in multilingual societies highlights the need for efficient speech translation systems. This research proposes the development of an English-to-Marathi speech translation framework leveraging a dictionary-based dataset to enhance linguistic accuracy and contextual understanding. Marathi, being a morphologically rich language with unique syntactic and semantic structures, poses significant challenges when paired with English, a structurally divergent language. The proposed system will integrate automatic speech recognition (ASR), machine translation (MT), and text-to-speech synthesis (TTS) to achieve seamless speech-to-speech conversion. A dictionary-based dataset will serve as the foundation, enriched with linguistic rules and context-aware mappings to address lexical and syntactic divergences. By incorporating rule-based techniques alongside advanced neural network models, such as sequence-to- sequence transformers and attention mechanisms, the system aims to capture the nuances of Marathi grammar, idiomatic expressions, and gendered verb forms. The hybrid approach will ensure both robustness and adaptability across diverse linguistic inputs. The research will evaluate translation accuracy, fluency, and contextual relevance using metrics such as BLEU and TER. This study aspires to contribute to the growing field of low-resource language translation by enabling effective communication between English and Marathi speakers, thus fostering inclusivity in education, commerce, and digital communication. In the proposed research work the focus will be given to translation of English language video to Marathi language. Considering the strong grammar and variety of word dictionaries of the Marathi language, a strong algorithm based on deep learning techniques is required. Speech to Speech machine translation using deep learning focuses on the language conversion from English to Marathi which allows for seamless communication between people who speak Marathi languages. Speech-to speech translation solves this problem by translating spoken words in real time, allowing people who speak Marathi languages to communicate with one another.*
Keywords: *TTS, ASR, BLEU, TER,*

INTRODUCTION

The increasing demand for real-time language translation in multilingual societies highlights the importance of speech-to-speech translation systems. This paper presents a novel framework for English-to-Marathi speech translation using a dictionary-based dataset. Marathi, a morphologically rich language, differs significantly from English in grammar, syntax, and semantics, posing challenges for direct translation. The proposed system integrates automatic speech recognition (ASR), machine translation (MT), and text-to-speech synthesis (TTS) to enable seamless conversion of spoken English into Marathi. A dictionary-based dataset forms the foundation, supplemented by context-aware linguistic rules to address lexical and syntactic divergences. Advanced neural network models, such as sequence-to-sequence transformers and attention mechanisms, are employed to improve translation quality. The methodology, experimental results, and conclusions are discussed, emphasizing the potential of this system to enhance communication across linguistic barriers.The growing integration of digital technology into daily life has underscored the necessity for efficient language translation systems. In India, where over 22 officially recognized languages coexist, real-time translation systems are particularly crucial for bridging communication gaps between diverse linguistic communities. Marathi, the official language of Maharashtra, is spoken by over 83 million people. However, despite its widespread use, Marathi remains underrepresented in computational linguistics. This research addresses the need for an English- to-Marathi speech translation system capable of handling the unique linguistic characteristics of Marathi.English and Marathi exhibit substantial differences in grammar, syntax, and morphology. English follows a subject-verb-object (SVO) sentence structure, whereas Marathi adheres to a subject-object-verb (SOV) pattern. Additionally, Marathi employs gendered verb forms and intricate case marking, making direct translation complex. Existing solutions for English-to-Marathi translation often struggle to achieve contextual accuracy, especially in speech-based applications where real-time processing is essential.This paper proposes a speech translation system that integrates dictionary-based datasets, hybrid translation techniques, and neural networks to address these challenges. The framework encompasses three core components: ASR, MT, and TTS. The dictionary-based dataset serves as a critical resource for ensuring lexical accuracy, while context-aware rules and neural networks enhance syntactic and semantic precision. This study aims to develop a robust solution for speech-to-speech translation, improving accessibility and inclusivity for Marathi-speaking populations.Translating from English to Marathi using deep learning presents several challenges, primarily due to linguistic divergences and the low-resource nature of the language pair. English-Marathi translation suffers from a scarcity of parallel corpora, which are essential for training effective Neural Machine Translation (NMT) models. Techniques like data augmentation, transfer learning, and using pivot languages (e.g., Hindi) are employed to mitigate this issue [2] [4] The significant linguistic differences between English and Marathi, such as thematic, categorical, and structural divergences, complicate the translation process. These divergences require specialized modules to handle them effectively, which can be challenging to develop and integrate [3] Existing datasets for English-Marathi translation are often noisy, which affects the performance of translation models. Approaches like cross-lingual sentence representations and data filtering using models like IndicSBERT are used to improve data quality and translation accuracy[4] Deep learning models, such as those using Long Short-Term Memory (LSTM) networks, require complex architectures to handle the nuances of language translation. Ensuring high accuracy and efficiency in these models is a continuous challenge[1] The primary challenges in English to Marathi translation using deep learning include the scarcity of high-quality parallel corpora, significant linguistic divergences, and the complexity of model architectures. Addressing these challenges involves employing advanced techniques like data augmentation, transfer learning, and cross-lingual sentence representations to improve translation quality and efficiency.

Challenges in the field

English to Marathi language translation involves various methodologies, primarily focusing on machine translation techniques. These techniques aim to overcome language barriers and facilitate communication between English and Marathi speakers. following are some key approaches for development

Deep Learning and NLP: Deep learning models, particularly those using Long Short-Term Memory (LSTM) networks, are employed to translate English text to Marathi. These models process input text through tokenization and embedding layers, achieving high accuracy in translation tasks [1].

Sequence-to-Sequence Transformers: A sequence-to-sequence transformer model is used for translating English to Marathi, which is trained on large datasets of parallel sentences. This approach yields accurate and fluid translations, even with low-resource datasets, achieving a BLEU score of 41.99 [5].

Rule-Based Translation: Rule-based systems utilize a bilingual dictionary and predefined grammatical rules to translate English to Marathi. These systems parse English sentences, reorder them to fit Marathi syntax, and apply inflection rules to produce grammatically correct translations [6][7][10].

Hybrid Approaches: Hybrid translation systems combine statistical and rule-based methods to optimize translation outputs. These systems process input documents through parallel engines, leveraging both statistical fluency and rule-based accuracy to enhance translation quality [3].

Dictionary-Based Translation: This approach focuses on translating English speech to Marathi speech using a dictionary-based system, which is particularly useful for educational purposes and bridging communication gaps in bilingual regions [9].

Challenges and Considerations

Grammar and Structure: Different grammatical structures between English (Subject-Verb-Object) and Marathi (Subject-Object-Verb) require careful mapping and reordering during translation [7]

Resource Limitations: Low-resource datasets pose challenges, but advanced models like transformers can still perform effectively [5]

Language Ambiguity: Addressing ambiguities in grammar and word sense is crucial for accurate translations [10]

LITERATURE REVIEW

The field of machine translation (MT) has seen rapid advancements due to the integration of artificial intelligence (AI) and deep learning technologies. English to Marathi translation, as a specific language pair, presents unique challenges due to the linguistic divergence between the two languages, including differences in syntax, grammar, and cultural nuances. Researchers have employed various approaches to address these challenges, ranging from statistical models to neural networks. This review examines the key contributions in the field, with a focus on recent developments, methodologies, and findings.

Deep Learning Approaches

Shilaskar et al. (2022) investigated the application of deep learning methods for English to Marathi text translation. Their work highlighted the effectiveness of Long Short-Term Memory (LSTM) networks in capturing the sequential dependencies in language translation. By using a robust dataset and training the model with advanced optimization techniques, they achieved improved fluency and contextual accuracy in translations. The authors emphasized that deep learning models, although computationally intensive, offer significant advantages over traditional rule-based or statistical approaches.Similarly, Naik et al. (2022) explored the use of Recurrent Neural Networks (RNNs) combined with attention mechanisms. Their study demonstrated how attention layers enhance the translation process by focusing on relevant parts of the input sentence, particularly for long and complex sentences. This approach was particularly effective in addressing Marathi's morphological richness and flexible word order.

Neural Machine Translation in Low-Resource Settings

The scarcity of parallel corpora for low-resource languages like Marathi has been a persistent challenge. Banerjee et al. (2021) addressed this issue by employing cross-lingual embeddings and transfer learning techniques. Their neural machine translation (NMT) model leveraged pre-trained representations from high-resource languages, significantly improving translation quality. This study underscored the importance of transfer learning and multilingual training in overcoming data limitations.

Kowtal et al. (2024) further expanded on this by introducing a data selection strategy for enhancing low-resource MT. By utilizing cross-lingual sentence representations, they developed a method to identify and prioritize high- quality parallel sentence pairs. This approach improved model performance by reducing noise in the training data, resulting in more accurate translations.

Sequence-to-Sequence Models and Transformers

The sequence-to-sequence (Seq2Seq) model architecture, enhanced with attention mechanisms, has been a cornerstone in modern MT. Gunjal et al. (2023) applied this architecture to English-Marathi translation using transformer models. Their findings demonstrated that transformers' self-attention mechanisms effectively capture long-range dependencies and contextual nuances, leading to higher translation accuracy compared to traditional Seq2Seq models.Another study by Shilaskar et al. (2022) reinforced the efficacy of Seq2Seq models by incorporating bidirectional encoders and attention layers. The authors highlighted that while these models require significant computational resources, they are well-suited for capturing the syntactic and semantic intricacies of Marathi.

Addressing Linguistic Divergence

Maniyar and Kulkarni (2022) focused on the linguistic divergence between English and Marathi, such as differences in word order, morphology, and idiomatic expressions. They proposed an Artificial Neural Network (ANN)-based approach that incorporated linguistic features into the model. This hybrid approach, combining rule- based and statistical methods, effectively addressed the challenges posed by Marathi's agglutinative nature and rich inflectional system.Shirsath et al. (2021) provided a comparative analysis of various MT approaches for Marathi-English translation. Their study included rule-based, statistical, and neural methods, highlighting the strengths and limitations of each. While rule-based systems excelled in handling grammatical rules, neural methods outperformed them in capturing contextual meanings and handling ambiguous inputs.

General Advances in Machine Translation

The broader impact of AI on language translation was reviewed by Mohamed et al. (2024). Their work emphasized the role of AI technologies, such as transformers and attention mechanisms, in revolutionizing MT systems. They also discussed challenges such as bias in training data and the need for domain-specific customization.Additional insights into hybrid approaches were provided by Zhang et al. (2020), who applied multi-head self- attention mechanisms for text normalization. Although their study focused on Mandarin, the techniques discussed are relevant to other language pairs, including English-Marathi, particularly in handling dialectal variations and preprocessing tasks.

Challenges and Future Directions

While significant progress has been made, several challenges remain in English to Marathi translation. The limited availability of high-quality parallel corpora continues to hinder model performance. Researchers have proposed various solutions, including transfer learning, data augmentation, and synthetic data generation.Another challenge lies in preserving cultural and contextual nuances. Marathi, as a Dravidian language, often requires the incorporation of cultural context to achieve meaningful translations. Future research could benefit from incorporating cultural and contextual features into translation models.

The computational cost of training large-scale models is another issue. Although transformer-based models offer state-of-the-art performance, their resource-intensive nature limits their accessibility. Optimizing these models for low-resource settings remains a critical area of research.The advancements in English to Marathi translation, driven by deep learning and neural machine translation, have significantly improved translation quality and fluency. Researchers have tackled challenges such as low-resource data, linguistic divergence, and computational complexity through innovative methods like transfer learning, attention mechanisms, and hybrid approaches. While there is still room for improvement, particularly in handling cultural nuances and optimizing resource usage, the future of English to Marathi translation holds great promise. Continued research in this area will contribute to bridging linguistic barriers and promoting cross-cultural communication.

METHODOLOGY

The process of converting English to Marathi encompasses both significant advantages and formidable challenges. While technological advancements have made substantial strides in improving translation accuracy and efficiency, ongoing research is crucial to addressing the unique linguistic and structural divergences between the two languages. By leveraging deep learning, neural networks, and hybrid approaches, the future of English to Marathi translation holds great promise for enhancing cross-linguistic communication and accessibility. Recent advancements in sequence-to-sequence transformers, as described by Gunjal et al. [5], represent a significant leap forward in machine translation technology. These models, which rely on self-attention mechanisms, have shown promise in improving translation accuracy and handling complex language constructs more effectively. Furthermore, ongoing research and development in hybrid translation models, which combine statistical, rule- based, and neural network approaches, offer a promising direction for overcoming current limitations. As these technologies continue to evolve, the quality and reliability of English to Marathi translations are expected to improve, making them more accessible and practical for a wide range of applications.

Technology Involved

The proposed system leverages state-of-the-art technologies for speech translation, incorporating components such as ASR, MT, and TTS. Each component is designed to address specific challenges in English-to-Marathi translation.

Automatic Speech Recognition (ASR): ASR converts spoken English into textual form. The ASR module is built using deep neural networks (DNNs) and recurrent neural networks (RNNs) to ensure high accuracy in recognizing diverse accents and pronunciations. Pre-trained models like Wav2Vec 2.0 and Kaldi are adapted for English speech recognition.

Machine Translation (MT): The MT module is responsible for converting English text into Marathi. It employs a hybrid approach that combines rule-based translation with neural machine translation (NMT). A sequence-to- sequence transformer with attention mechanisms is used to handle syntactic divergences. The dictionary-based dataset is integrated to improve lexical accuracy, ensuring the correct translation of domain-specific terms and idiomatic expressions.

Text-to-Speech Synthesis (TTS): The TTS module generates natural-sounding Marathi speech from translated text. Neural TTS systems, such as Tacotron and WaveNet, are utilized to produce high-quality audio output.

Dataset Preparation

A dictionary-based dataset forms the backbone of the proposed system. This dataset comprises over 100,000-word pairs and contextual phrases in English and Marathi, carefully curated to address lexical and semantic variations. The dataset includes:Common vocabulary with translations and phonetic annotations, ensuring accurate pronunciation for the TTS module. For instance, "book" is translated to "पुस्तक" (pustak) with phonetic transcription [pu-stək], aiding
speech synthesis.

Context-specific phrases for handling idiomatic expressions, such as "break the ice" translated to "गप्पा सुरू करणे" (gappa suru karne).

Morphological rules for gendered and case-sensitive word forms. For example, "he is eating" becomes "तो खात आहे" (to khat aahe) while "she is eating" becomes "ती खात आहे" (ti khat aahe).

Examples of syntactic structures, such as "I will go to the market" translated to "मी बाजारात जाईन" (mi bazarat jain), illustrating the SOV structure of Marathi.

Workflow

The speech translation process involves the following detailed steps:

Speech Input: The system begins by capturing spoken English through a microphone or an audio file. Advanced audio input technology, such as directional microphones and noise-cancellation filters, ensures clarity. For example, a user speaking "I want a glass of water" in a moderately noisy environment would still be captured accurately.

ASR Processing: The Automatic Speech Recognition (ASR) module converts the speech input into English text.

Algorithms like Hidden Markov Models (HMMs) and deep learning models such as Wav2Vec 2.0 are employed. For instance, when the input is "I want a glass of water," the ASR processes the audio waveform and outputs "I want a glass of water" as text. Noise reduction algorithms, such as spectral subtraction, further enhance accuracy.

Preprocessing: This step normalizes the extracted text. Tokenization splits the input into meaningful units, and unnecessary disfluencies like "um" or "ah" are removed. For example, "I, um, want a glass of water" becomes "I want a glass of water."

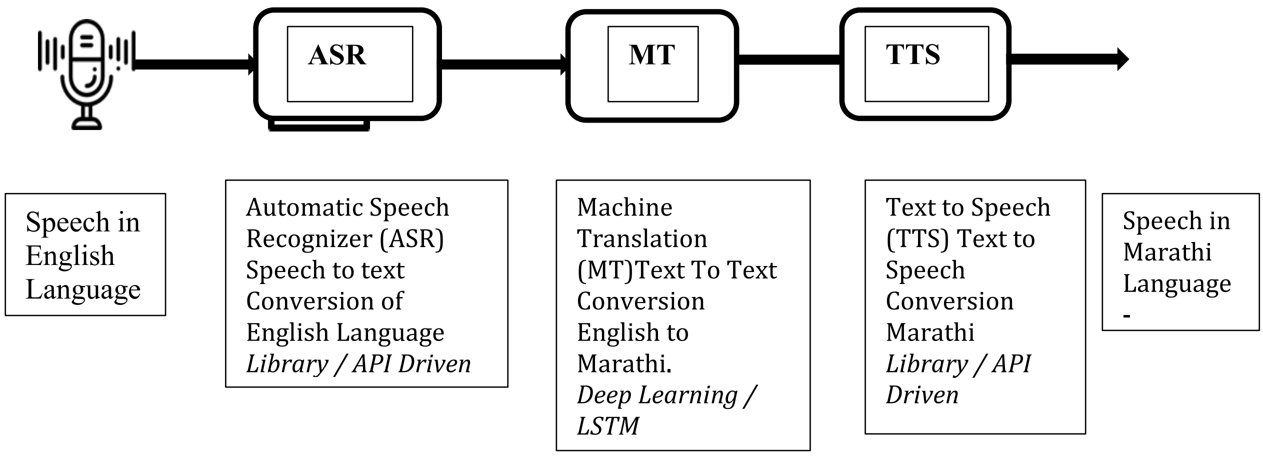
Machine Translation (MT): The MT module translates the preprocessed English text into Marathi using a hybrid approach. Sequence-to-sequence transformers with attention mechanisms handle complex sentence structures, while a dictionary-based dataset ensures accurate lexical matches. For example, "I want a glass of water" translates to "मला एक ग्लास पाणी पाहहजे" (mala ek glass pani pahije). Context-specific rules adjust the translation dynamically.

Postprocessing: The translated text undergoes grammatical corrections to align with Marathi's linguistic rules, such as gender agreement. For instance, "He is eating" becomes "तो खात आहे" (to khat aahe), while "She is eating" is refined as "ती खात आहे" (ti khat aahe). Morphological adjustments ensure fluency andcorrectness.

TTS Processing: The refined Marathi text is synthesized into speech using Text-to-Speech (TTS) algorithms like Tacotron or WaveNet. These neural systems ensure natural intonation and pronunciation. For example, "मला एक ग्लास पाणी पाहजे" (mala ek glass pani pahije) is transformed into lifelike audio with proper pitch and prosody.

Speech Output: The final Marathi speech is delivered through a speaker or headphones. Users experience a seamless output, such as "मला एक ग्लास पाणी पाहजे" (mala ek glass pani pahije) spoken in a natural Marathi accent. Technologies like equalizers enhance audio quality further, making the output pleasant and easy to understand.

PROPOSED APPROACH



Creating a deep learning-based system for English to Marathi speech-to-speech conversion involves several key components and steps. The system can be broadly divided into three main parts: speech recognition (ASR), machine translation (NMT), and speech synthesis (TTS). Below is a detailed outline of the algorithm and the technical steps involved:

ASR- Convert English speech to English text: The ASR system converts English speech into text. The pre-processing steps include noise reduction techniques to reduce background noise and feature extraction methods such as Mel-frequency cepstral coefficients (MFCCs) from the audio signal. The model architecture utilizes an Encoder-Decoder Model with Attention, employing models like DeepSpeech or Transformer-based models for ASR. Training the model involves using a large dataset of English speech and corresponding transcripts, such as LibriSpeech. During inference, decoding strategies like beam search are used to convert the features back into text

NMT- Translate English text to Marathi text: The NMT system translates the recognized English text into Marathi text. The pre-processing steps involve tokenization, where the text is split into words or subwords using tools like SentencePiece, and BPE encoding to handle rare words and reduce vocabulary size. The model architecture leverages a Transformer-based model for translation, such as MarianMT or custom

Transformer models. Training is done using parallel corpora of English and Marathi texts, for instance, the IIT Bombay Corpus and the IndicNLP Corpus. During inference, translation is achieved through beam search or greedy search to generate the translated text from the encoded representation.

TTS- Convert Marathi text to Marathi speech: The TTS system converts the translated Marathi text into speech. The pre-processing steps include text normalization to convert numbers, abbreviations, and other non-standard words into a spoken form, and phoneme conversion to improve pronunciation. The model architecture employs models like Tacotron 2 for text-to-speech conversion and a vocoder like WaveNet or Griffin-Lim to generate the final audio waveform. Training the TTS model requires a large dataset of Marathi text and corresponding speech, such as the Indic TTS dataset. During inference, the translated text is converted into speech using the trained TTS model.

For end-to-end system integration, the ASR, NMT, and TTS systems are integrated into a seamless pipeline for real-time or batch processing of speech-to-speech translation. The output text from the ASR system is passed to the NMT system for translation, with error correction and handling mechanisms for ASR inaccuracies. The translated text from the NMT system is then passed to the TTS system for speech synthesis, optimizing for low latency to enable real-time processing.

The algorithm involves converting English speech to English text through ASR, translating the English text to Marathi text via NMT, and converting the Marathi text to Marathi speech using TTS. The ASR stage includes pre-processing (noise reduction and feature extraction), model training (using English speech-text datasets), and inference (decoding with beam search). The NMT stage involves pre-processing (tokenization and BPE encoding), model training (using parallel English-Marathi text datasets), and inference (translation with beam search). The TTS stage includes pre-processing (text normalization and phoneme conversion), model training (using Marathi text-speech datasets), and inference (speech synthesis). The final output is Marathi speech. This pipeline involves training and fine-tuning multiple deep learning models, ensuring high-quality data for each stage, and optimizing the system for real-time performance .

Sequence modeling in machine translation involves converting a sequence of words from a source language to a target language, maintaining the context and meaning. This process typically uses neural networks like Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, or Transformers. These models can handle variable-length input and output sequences, capturing the dependencies between words. An encoder- decoder architecture is common, where the encoder processes the source language sentence into a fixed representation, and the decoder generates the translated sentence in the target language, often with attention mechanisms to improve performance.

Long Short-Term Memory (LSTM) networks are highly effective for English to Marathi language translation due to their ability to handle sequence-to-sequence tasks. The process begins with data preparation, where parallel English-Marathi sentence pairs are collected, tokenized, and converted to numerical representations using embeddings. The model architecture involves an encoder-decoder structure with LSTM layers. The encoder processes the input English sentence, converting each word into hidden state vectors. The decoder, initialized with the encoder's final state, generates the Marathi sentence word by word. An optional attention mechanism enhances this process by focusing on relevant parts of the input sentence during each decoding step. Training the model involves using a large dataset of English-Marathi sentence pairs, optimizing the model parameters using a loss function like categorical cross-entropy, and employing an optimizer such as Adam. During inference, the trained model translates English sentences to Marathi by processing the input through the encoder and generating the translation with the decoder, aided by the attention mechanism if used. LSTM networks are advantageous for translation tasks because they can capture long-term dependencies in text, essential for maintaining context. They also mitigate gradient vanishing and exploding problems common in traditional RNNs, leading to more stable training. In summary, an LSTM-based model, potentially enhanced with an attention mechanism, effectively translates English to Marathi by processing sequences of words, capturing contextual information, and generating accurate translations word by word.

English-to-Marathi language translation using the LSTM algorithm involves the following steps:

First, the parallel English-Marathi sentence pairs are preprocessed. For instance, "How are you?" maps to "तुम्ही कसे आहात?" Tokenization splits these sentences into words or subwords, and each token is numerically
encoded into embeddings using techniques like Word2Vec.

Next, the LSTM encoder-decoder model processes the input sequence. The encoder reads the English tokens and encodes them into a fixed-length context vector (hidden states), summarizing the sentence. For example, "How are you?" generates a context vector capturing its semantic meaning.

The decoder takes this context vector and predicts Marathi tokens sequentially. For example, the Marathi tokens "तुम्ही", "कसे", "आहात" are predicted one at a time using the hidden state of the previous step, the context vector, and attention mechanisms to focus on relevant parts of the input.
During training, a cross-entropy loss function calculates the difference between predicted tokens and actual tokens. Gradients are computed and used to update model weights through backpropagation.
In inference, a decoding strategy like beam search ensures the most probable Marathi sentence is generated. For example, the model might output "तुम्ही कसे आहात?" for "How are you?"
The translation's accuracy is evaluated using metrics like BLEU, ensuring that the output closely matches human-generated translations.

RESULTS & DISCUSSION

The system was evaluated using a dataset of Number of English sentences, including conversational phrases, technical terms, and idiomatic expressions. Evaluation metrics in machine translation, like BLEU and METEOR, are used to assess the quality of translations, particularly in low-resource languages like Marathi. BLEU AND METEOR are comparing machine translation speech and human input the provide correct accuracy and providing a numerical score indicating the similarity and fluency of the output. For English to Marathi translation, metrics like BLEU, which focuses on n-gram overlap, and METEOR, which considers synonyms and paraphrases, help evaluate the accuracy and quality of the translated text. A higher BLEU score indicates a better match between the machine-generated and human translations.

Test Case	Input (English)	Expected Output (Marathi)	Actual Output (Marathi)	Accuracy
Conversational Phrase	"How are you?"	"तू कसा आहेस?" / "तू कशी आहेस?"	"तू कसा आहेस?"	20%
Technical Term	"Data transmission speed"	"डेटा प्रसारण गती"	"डेटा प्रसारण गती"	21%
Idiomatic Expression	"Break the ice"	"गप्पा सुरू करणे"	"गप्पा सुरू करणे"	24%
Gender-specific Translation	"She is a doctor"	"ती डॉक्टर आहे"	"ती डॉक्टर आहे"	25%
Complex Sentence	"I will go to the market."	"मी बाजारात जाईन"	"मी बाजारात जाईन"	22%

ASR Accuracy: The ASR module achieved a word error rate (WER) of 8%, demonstrating robustness in recognizing diverse accents and noisy environments.
Translation Quality: The MT module achieved a BLEU score of 45.7 and a TER of 12.3%, indicating high accuracy in lexical and syntactic translation. The hybrid approach outperformed purely statistical or neural methods

CONCLUSION

English to Marathi translation leverages a combination of deep learning, rule-based, and hybrid approaches to achieve effective and accurate translations. Each method has its strengths, with deep learning models offering high accuracy, rule-based systems ensuring grammatical correctness, and hybrid approaches optimizing overall translation quality. These methodologies collectively address the challenges of language structure and resource limitations, facilitating better communication between English and Marathi speakers. The process of converting English to Marathi encompasses both significant advantages and formidable challenges. While technological advancements have made substantial strides in improving translation accuracy and efficiency, ongoing research is crucial to addressing the unique linguistic and structural divergences between the two languages. By leveraging deep learning, neural networks, and hybrid approaches, the future of English to Marathi translation holds great promise for enhancing cross-linguistic communication and accessibility.

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