RESEARCH PAPER

A Low-Resource NLP Framework For Bilingual Next-Word Prediction In Tamil In Assistive Technology

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Abstract— This study focuses on improving next-word prediction for Tamil, a low-resource language, within Assistive Technology. Limited availability of annotated Tamil language data poses a major challenge for building accurate predictive models. To address this, a bilingual prediction framework is proposed that uses Tamil–English translation to take advantage of the richer linguistic resources available in English. Pre-trained translation models are integrated with language models such as LSTM, BiLSTM, GRU, and BERT to enhance prediction performance in AAC applications. The models are evaluated across sentences of varying lengths, including short, medium, and long utterances commonly used by AAC users. Experimental results show that recurrent neural models perform consistently across all sentence lengths, with GRU achieving the highest precision for short sentences. To reduce semantic loss during translation, neural machine translation techniques designed to preserve contextual meaning are employed, leading to improved prediction accuracy and contextual relevance. The proposed framework demonstrates effective semantic retention, achieving a BLEU score of 0.75 for short sentences. Overall, the bilingual approach improves next-word prediction quality and supports more natural communication in AAC systems. The framework is scalable to other low-resource languages and provides a foundation for future real-world user evaluation and the integration of advanced generative language models to further enhance predictive performance.

Keywords— Next-word prediction, Augmentative and Alternative Communication (AAC), Bilingual framework, Tamil-English translation, Low-resource language, Multilingual AAC applications

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1. Introduction

Tamil is recognised as one of the oldest classical languages in the World, with a high literary history spanning over 2000 years. Tamil is a morphologically rich language with a complex system of verbs, conjugations, particles and pre-/postpositions adjectives and adverbs [1]. This complexity makes Tamil an ideal candidate for testing and advancing the natural Language Processing models [2]. Tamil is classified as a low-resource language in the field of Natural Language Processing (NLP), primarily due to the lack of large-scale annotated datasets, pre-trained models, and computational tools [3]. This scarcity of digital resources obstructs the development of effective NLP applications, such as machine translation, text generation, and next-word prediction, for Tamil. As a result, Tamil remains underrepresented in modern language technologies, limiting its accessibility and integration into digital platforms [4], [5]. Many tools and applications have been developed for English and other major global languages, leaving a gap in technological accessibility for speakers of low resource languages like Tamil. According to UNESCO, Tamil is spoken by over 70 million people worldwide, with a significant number facing speech impairments requiring AAC devices. However, AAC applications often exclude Tamil, limiting their usability. For example, AAC tools like Avaz provide basic Tamil support but lack context-aware next-word prediction and adaptive learning, leaving critical gaps in accessibility and communication.

Many Tamil-speaking individuals have difficulty conversing in Tamil due to disabilities which include Articulation Disorders, Fluency Disorders, Voice Disorders and Language Disorders. [6] declares that these disorders are caused by Genetic predisposition, Neurological Disorders, Hearing Loss, Trauma and Developmental delays. Augmentative and Alternative Communication (AAC) Devices support individuals with speaking difficulties. AAC devices are categorised into Unaided Communication Systems, Aided Communication Systems, Low-tech Devices, High-Tech Devices, Specialized Devices, Portable Devices and Progressive Devices. Out of these systems, the tools used in High-Tech, specialised, portable, and progressive devices in this technological era provide comfort for the speakers. High-Tech Devices include Speech-Generating Devices (SGD) that help speech-impaired individuals to communicate [7].

[8] give some examples of SGD such as Mobiles or Tablets with specialised applications, Eye-tracking devices, Dynamic display devices, and Computer-based systems. The specialised applications are the AAC mobile applications including Proloquo2Go, Proloquo4Text, Avaz, CoughDrop, Lamp and many more. These SGDs are available primarily in English and a few other languages which include Spanish, French, Arabic, Chinese, Czech, Danish, Dutch, Finnish, French, German, Greek, Hebrew, Hindi, Hungarian, Italian, Japanese, Korean, Norwegian, Polish, Portuguese, Russian, Spanish, Swedish, and Turkish. Certain languages, such as Tamil and many other regional Indian languages categorized as low-resource languages, are not supported by these applications. Thus, effective communication remains a significant challenge for Tamil-speaking individuals with speech difficulties and their communication partners.

In the domain of AAC, Tamil-speaking individuals with speaking difficulty face significant challenges due to the limited availability of AAC systems that support Tamil. Most AAC tools are designed for high- resource languages like English, leaving Tamil speakers with few or inadequate options. The complexity of Tamil's agglutinative structure, extensive verb conjugations, and the presence of multiple dialects pose significant challenges for integrating the language into AAC systems. These intricacies require tailored models that can accurately predict contextually appropriate words or phrases. This study leverages bilingual frameworks to utilize English's abundant resources while addressing

Tamil's linguistic nuances, making it a viable solution for low-resource contexts where direct Tamil NLP models face data scarcity. This lack of linguistic support in AAC systems intensifies communication barriers, preventing Tamil-speaking individuals with speaking difficulty from fully participating in social, educational, and professional activities [9], [10]. The next-word prediction feature in AAC applications significantly enhances communication by improving the speed, efficiency and accessibility for the individuals with speaking difficulty [21]. The absence of accurate next-word prediction and language-specific features in AAC applications for Tamil further limits their effectiveness, highlighting the urgent need for modified solutions to bridge this gap. This paper also highlights the need for adaptive learning mechanisms in AAC applications to personalize next- word predictions for individual users, enhancing communication efficiency and usability.

A framework has been proposed to bridge the communication gap between Tamil-speaking individuals with speech disabilities and their communication partners. This framework incorporates translation from a low-resource language to English followed by the next-word prediction to make ease of use of the application and tailored by the reverse translation phase from English to Tamil. Related works are discussed in the following session, followed by the methodology and then the results and discussions finally the conclusion.

2. Related Works

This session explores related works on the challenges faced by individuals with speaking difficulties, followed by an examination of assistive technologies that support communication. It investigates the use of AAC devices as a key assistive technology, with a particular focus on language support in AAC mobile applications, especially in low-resource languages. The session also highlights recent technical advancements in AAC applications and discusses existing frameworks for language translation in low- resource contexts. Also, studies on the effectiveness of next-word prediction models are reviewed to exhibit their role in enhancing communication. The session concludes with an analysis of the challenges involved in developing AAC applications for individuals with speech difficulties within the Tamil-speaking community.

Speaking is a unique human ability used for communication. This involves the articulation of sounds to convey thoughts, emotions, and information. Speaking is an essential aspect of human life. It serves as the primary mode of communication [11]. There is difficulty in speaking because of cultural and linguistic identity, cognitive and developmental delays, and physical and neurological limitations. As a result, the expression of thoughts, emotions, and needs leads to misunderstanding and social isolation. This leads to limited ability to participate in conversations, making everyday interactions challenging [12]. Addressing these challenges requires assistive technology to support individuals with speaking difficulties in various aspects of life.

[13] defines Assistive Technologies (AT) as any device, system or equipment designed to assist individuals with disabilities. AT is used to enhance the quality of life independence, and functional abilities. One of the key aspects of assistive technology includes communication support [14]. For individuals with speaking difficulty, AT often includes Augmentative and Alternative Communication (AAC) devices, such as communication boards, tablets and mobiles with specialized applications, or eye-tracking systems. [15] These devices help individuals express themselves when they have difficulty speaking. These tools pave the way for promoting inclusivity and equal opportunities to participate fully in society despite their difficulty. Mobile applications as one of the AAC devices are categorized under hi-tech aided AAC devices [16]. This includes many mobile applications that support individuals with speaking difficulties. These mobile applications include Proloquo2Go, Proloquo4Text, Avaz, CoughDrop, Lamp and many more [17]. Table 1 compares the existing AAC tools with the proposed framework.

Table 1
Comparison of Existing AAC Tools with the Proposed Framework

Tool	Language Support	Next-Word Prediction	Adaptive Learning	Tamil Support	Multilingual Support
Proloquo 2Go	English, Spanish, French, etc.	Limited	No	No	Yes
Proloquo 4Text	English, Spanish, French, etc.	Limited	No	No	Yes
Avaz	English, Hindi, Tamil	Basic (rule-based)	No	Yes	Yes
CoughDrop	English, Spanish, French	Basic (rule-based)	Limited (basic customization)	No	Yes
LAMP Words for Life	English	Limited	No	No	No
Snap + Core First	English, Spanish, French	Basic (rule-based)	No	No	Yes
GoTalk NOW	English, Spanish	No	No	No	Yes

Grid for iPad	English, Spanish	Limited	No	No	Yes
Lingraphica	English	No	No	No	No
Predictable	English, Spanish, French	Basic	No	No	Yes
Voice4U AAC	English, Japanese	Limited	No	No	Yes
Tobii Dynavox Communicator 5	English, Spanish, French	No	No	No	Yes
DynaVox Compass	English, Spanish	Basic	No	No	Yes
EasyTalk	English, Dutch	No	No	No	Limited
LetMeTalk	English, Spanish	No	No	No	Yes
Jellow	English, Hindi, Bengali	No	No	No	Yes
Assistive Express	English	Limited	No	No	No
ClaroCom	English, Spanish	No	No	No	Yes
AAC Autism Talk Now	English	No	No	No	No
Proposed Framework	Tamil, English	Advanced (neural models: GRU, LSTM, BiLSTM)	Planned (context-aware adaptation)	Yes	Yes (bilingual)

The use of these AAC mobile applications has a significant growth in recent years due to the advancements in technology. The AAC mobile applications are designed to help individuals with speaking difficulty to communicate with more effective alternative means of expression [18]. These applications are particularly beneficial for those with conditions such as cerebal palsy, autism, stroke and other neurological disorders that impair their verbal communication [15]. The AAC mobile applications act as speech- generating devices. The key features of these applications include producing speech. These applications allow users to input text through touch, typing or even voice recognition. It can be customized to meet the user's specific needs [18]. Some applications like Proloquo2Go, Proloquo4Text, Avaz, CoughDrop, Lamp and many more support multiple languages. These applications provide enhanced communication, increased independence, cost-effectiveness, portability and convenience [19].

Language support in AAC mobile applications has become essential for individuals who require communication in specific linguistic contexts. The multilingual support enables the individuals to communicate effectively in their preferred languages. This enhances their ability to interact with various social and cultural environments. Indian regional languages that are low-resource languages include Tamil, Telugu, Punjabi, Urdu, Gujarati and many more [20]. Low-resource languages often lack the availability of linguistic resources, such as digital corpora, text data, and language processing tools, these result in several challenges when designing the AAC mobile applications. The challenges include limited lexicons and insufficient speech recognition tools [9]. There are some developmental efforts in developing low-resource language AAC mobile applications which include creating symbol sets and gathering insights from the user feedback. A comparison with AAC tools like Avaz highlights that while these applications provide basic Tamil support, they lack adaptive learning and context-aware next-word prediction features, which are essential for effective communication. Unlike our proposed framework, these tools do not utilize bilingual translation or advanced neural models for prediction, limiting their usability for Tamil-speaking individuals.

The development of the AAC mobile application that supports the Tamil language faces several obstacles. That is limited digital resources like comprehensive vocabulary datasets [21]. Then the inadequacy of symbol libraries that accurately represent the language and cultural context. And the challenges in incorporating cultural expressions, idioms, and symbols relatable to Tamil speakers [22]. AAC mobile applications like AVAZ focus on providing support for Tamil-speaking individuals. Though language support is being provided with the advancement in technology, it is still lacking in features such as inadequate symbol libraries, limited adaptive learning, low accuracy in next-word prediction models and advanced speech synthesis [23]. However, existing studies do not fully address the need for preserving Tamil-specific idiomatic expressions or handling regional dialects in AAC systems. This gap highlights the urgency for frameworks that can bridge linguistic and cultural nuances.

Table 2 presents research papers that summarizes the model used by various researchers for next word prediction. [3] propose the effectiveness of next-word prediction models in AAC mobile applications as a key factor in enhancing communication for individuals with speaking difficulty. Next-word prediction models work by analyzing the previous inputs from the user and employing statistical methods or Machine Learning techniques. Common approaches include N-gram modelling, neural network models such as Long Short-Term Memory (LSTM) or Bidirectional LSTM (BiLSTM), and Gated Recurrent Unit (GRU). LSTM models are specifically designed to handle long-term dependencies, making them suitable for tasks involving time-series data or sequential information [21], [24]. BiLSTM extends this capability by processing data in both forward and backward directions, which enhances context understanding. This leads to improved prediction accuracy, especially in tasks where the relationship between historical and future data points is significant [20]. The unique bidirectional architecture of BiLSTM, which processes input sequences in both forward and backward directions, enables it to capture contextual information more effectively than unidirectional models [24]. This capability is especially valuable for next-word prediction tasks, where understanding the complete context of a sentence is essential for accurate predictions. Traditional LSTM architectures have also proven effective for language modelling, surpassing standard feed-forward networks by accounting for entire sequences of preceding words [25]. By addressing the limitations of fixed context lengths essential in earlier models, LSTMs are particularly well-suited for complex tasks like next-word prediction. Optimizing LSTM architectures, such as through hyperparameter tuning or architectural adjustments, has improved performance significantly, particularly in perplexity—a common metric for evaluating language model accuracy [25].

GRUs, on the other hand, simplify the LSTM architecture by combining the forget and input gates into a single update gate, which makes them more computationally efficient while still capturing long-term dependencies [26]. The integration of GRUs into sequence-level training algorithms significantly enhances the robustness and accuracy of next-word predictions, aligning with the demand for high-quality text generation [27]. One of GRU's strengths lies in its efficiency, which is often highlighted as a key factor in its performance. While LSTMs may achieve lower word error rates in tasks like automatic speech recognition, GRUs offer faster optimization with comparable performance levels [28]. This efficiency becomes particularly crucial in real-time applications, where rapid predictions are necessary, positioning GRUs as a viable choice for next-word prediction in resource-constrained environments [26]. In experiments, GRUs have shown comparable performance to LSTMs but with lesser computational costs, especially in complex applications. BERT introduces a different approach to processing language data with its transformer architecture, allowing it to capture contextual relationships in words effectively. [15] advise that the integration of contextual AI helps in understanding the context and the user intent which can lead to more accurate predictions and richer communication experiences.

TABLE 2
MODELS USED IN VARIOUS RESEARCH FOR NEXT WORD PREDICTION.

Category	Model/Approach	Functionality	Advantages	Key References
Traditional Models	N-gram Modeling	Predicts the next word using statistical probabilities based on the occurrence of the preceding n-1 words.	Simple, interpretable, suitable for basic prediction tasks.	[3]
Recurrent Networks	LSTM	Handles long-term dependencies through memory cells and gating mechanisms.	Reduces errors in sequential tasks, especially for long contexts.	[21], [24], [25]
	BiLSTM	Processes data in both forward and backward directions to enhance context understanding.	Improves accuracy by capturing bidirectional context in sequential data.	[20], [24]
	GRU	Simplified LSTM architecture with reduced computational complexity by combining input and forget gates into one.	Efficient for real-time and resource-constrained environments while maintaining competitive accuracy.	[26], [27], [28]
Transformer Models	BERT	Uses bidirectional attention mechanisms to capture contextual relationships in a sentence.	Excels in understanding context and user intent, supporting rich communication experiences in AAC applications.	[29], [30], [31]
Performance Enhancers	Optimization Techniques	Methods like hyperparameter tuning and architectural modifications to	Improves performance metrics such as perplexity, reduces word error rates, and tailors	[24]

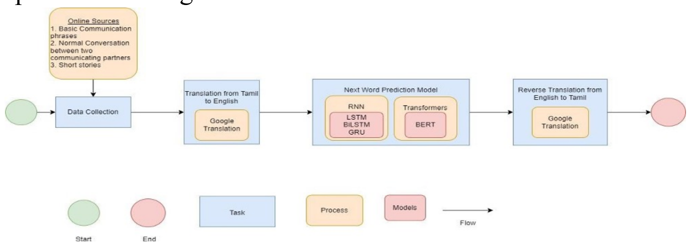
		optimize model performance for specific tasks.	models to specific application needs.	

The development of AAC mobile applications in low-resource languages presents several challenges for developers, particularly in areas such as Natural Language Processing (NLP), machine translation, and application design. For instance, Tamil poses unique difficulties due to its complex script and diverse dialects [20]. The complexities of Tamil grammar and syntax may require custom dictionaries and symbol sets. [32] address the complexities of using low-resource languages few frameworks have been proposed by various researchers implementing language translation. One of the primary frameworks is Neural Machine Translation (NMT). This uses artificial neural networks to translate the text. NMT systems incorporate transfer learning from high-resource languages to improve translation for low-resource languages. [33] proposes another framework Multimodal Machine Translation (MMT) incorporates multiple modalities which include: text and images to support the translation task. This framework enhances the context and accuracy of translations. Back-translation involves translating the text into a different language and back to the original language. [34] [35] discuss a specific initiative, such as the Workshop on Machine Translation (WMT) shared tasks focused on low-resource Indic languages. This provides structured frameworks for developing and evaluating various translation systems. In these tasks, the participants are encouraged to create machine translation systems for language pairs like English-Assamese and English-Manipuri using datasets like IndicNE-corp1.0. This initiative fosters collaboration and innovation within the field, helping to raise awareness and improve translation quality for underrepresented languages.

A significant research gap exists in developing AAC mobile applications for low-resource languages such as Tamil. Despite advancements in AAC technologies, Tamil faces unique challenges due to limited linguistic resources, including insufficient lexicons, digital corpus, and language processing tools. This hinders the development of effective AAC solutions [20], [21]. Additionally, the lack of culturally and linguistically appropriate symbol libraries and the challenges in capturing Tamil's complex grammar, and idiomatic xpressions further complicate the design of effective AAC systems [22]. Current AAC applications like Avaz provide Tamil support but lack adaptive learning mechanisms, which could personalize next-word prediction based on user-specific preferences, limiting their effectiveness. The next- word prediction models like LSTM, BiLSTM, and GRU, though promising, remain under-optimized for Tamil, often lacking in accuracy and contextual understanding [3]. Moreover, existing frameworks for machine translation, such as Neural Machine Translation (NMT) and Multimodal Machine Translation (MMT), have yet to be fully applied to enhance AAC functionality in low-resource languages [33]. Finally, the lack of adaptive learning features and personalized vocabulary expansion in current AAC applications, like Avaz, limits their potential for diverse user needs [23]. This gap highlights the need for research focused on developing culturally sensitive, multilingual AAC tools, incorporating advanced machine learning, and improving language support for Tamil and other low-resource languages.

3. Methodology

This section details the proposed framework to bridge the communication gap for Tamil-speaking individuals with speaking difficulties. Fig. 1 illustrates the method flow of the model construction. The main inputs are user-controlled vocabulary, day-to-day conversation phrases and complete story lines. The data collections are detailed in the first session of the methodology followed by the translation from Tamil – low resource language to English, followed by the next word prediction and finally the reverse translation of the predicted phrase from English to Tamil.



A. Data Collection

B. Fig. 1. Flow chart for model construction

The first step in the framework involves collecting data that reflects real-world usage of Tamil in different contexts. The collection of sentences was in various lengths. They are collected from various online sources. The collected sentences were categorized as Category 1 (C1) which has less than 5-word sentences, then Category 2 (C2) which has 6 to 10-word sentences and Category 3 (C3) which has more than 10-word sentences.

C1 is collected from various online sources which are basic communication phrases in colloquial Tamil. These sentences typically consist of basic communication phrases that are commonly used in daily conversations, such as greetings, commands, or simple queries. These phrases were taken from https://www.linguanaut.com/learn-tamil/phrases.php. These phrases are gathered from online sources that provide colloquial Tamil used in everyday interactions. This dataset helps the model handle basic sentence structures, where the prediction task is relatively straightforward. AAC users often rely on quick and simple phrases such as greetings (e.g., "வணக்கம்"), commands (e.g., "வாங்க"), or basic queries (e.g.,"என்ன?"). These phrases are critical for daily interactions, especially for individuals with limited language proficiency or cognitive challenges.

C2 sentences are also collected from online sources which are normal colloquial conversational phrases between two communicators. This is taken from https://ilearntamil.com/32-conversations-in-colloquial- tamil-and-english/. This category captures typical conversational exchanges, including statements or questions that involve moderate complexity, such as subject-verb-object structures. These sentences are more diverse in terms of syntax and may introduce new vocabulary or idiomatic expressions. Data is sourced from common conversational Tamil between two communicators, providing a more realistic representation of conversational flow. Real-world conversations often involve slightly longer and more nuanced exchanges. For example, a sentence like "உங்களுக்கு என்ன வேணும், டீ-ஆ இல்ல காபியா?" ("What do you need, tea or coffee?") requires the AAC system to understand context and word relationships.

C3 sentences are framed from short Tamil stories that were in colloquial language, and taken from https://tamilkathaigal.com/category/tamil-short-story/. Long sentences typically involve narratives or more detailed expressions. These sentences are complex, incorporating clauses, conjunctions, and more sophisticated syntactic structures. Data for these sentences is drawn from short stories or articles in colloquial Tamil, providing rich context that can assist in improving next-word prediction accuracy when more information is available. Although this dataset primarily represents standard colloquial Tamil, future efforts must incorporate regional dialects to enhance linguistic diversity and improve usability for a broader audience. Future work will prioritize collecting datasets from various Tamil dialects, including Kongu Tamil, Madurai Tamil, and Sri Lankan Tamil, to account for regional linguistic differences. Expanding the dataset to include regional dialects, such as Kongu Tamil and Eelam Tamil, will enhance the framework's adaptability and relevance. This will involve community collaborations to collect diverse linguistic data while ensuring cultural sensitivity. For users who communicate complex ideas or narrate events, the AAC system must handle longer sentences with intricate structures. For instance, a sentence like "ஒரு நாள், நான் பூங்காவிற்குச் சென்று அந்த பொண்ண பார்த்துவந்தேன்" ("One day, I went to the park and saw that girl") requires understanding of context, syntax, and relationships between clauses. Table 3 has the examples for each category.

TABLE 3
EXAMPLES FOR EACH CATEGORY

Category	Tamil Sentence	Translated Sentence
C1 (<5 words)	நான் இங்வக நிணறய வாங்கிவனன்.	I bought a lot here.
C2 (6–10 words)	வாங்கம்மா! இங்க வந்து உக்காருங்க. சொல்லுங்க, என்ன பிரச்சணை?	Hi, come and sit here. What's your problem?
C3 (>10 words)	உன்னோட வண்டி அடிக்கடி பஞ்சர் ஆகுது அதனால இந்த மாச சம்பளம் வாங்குன உடனே டயர்-அ மாத்து.	Your bike is getting punchered very often. So once you get your salary change the tyre.

The variation in data collection serves several key purposes in improving the quality and performance of the model, especially for tasks like translation or next-word prediction. After categorization, the dataset is passed on into the translation phase from Tamil to English. Categorizing sentences by length allows the model to learn and handle different levels of linguistic complexity. This categorization of sentences into three groups is done to better align the model's capabilities with different communication needs of AAC users. This approach is essential in Addressing User Needs Across Communication Scenarios. This approach reflects the varied sentence structures found in the real world conversations. This system ensures in adapting to different contexts, such as quick expressions of basic needs, structured queries or detailed story telling by the individuals with speaking difficulty. By categorizing the data, this proposed framework allows for targeted training of next-word prediction models by improving their performance. This enhances the accuracy, the context awareness and personalization of the AAC system. This makes it more inclusive and effective for individuals with speaking difficulties.

C. Translation from Tamil to English Process

The next step in the framework is translating the Tamil input sentence into English. This step uses the vast resources available for English, such as large-scale pre-trained models, word embeddings, and linguistic tools [34]. For AAC applications, this step is instrumental in enhancing the communication for individuals with speaking difficulty. This translation process ensures that the model can utilize English-language prediction capabilities, which are often more advanced than those for Tamil due to the abundance of English-language datasets [20]. The translation model used here is based on advanced neural machine translation (NMT) techniques, such as transformer models, which excel at handling the intricacies of language structure and syntax. By converting the Tamil input to English, the model benefits from the larger pool of resources available for English, improving its prediction accuracy [32]. For instance, the Tamil phrase 'அவள் பூச்சி பார்த்தாள்' ('She saw a bug') was translated into English and back to Tamil without altering its semantic meaning, demonstrating the model's capability to handle complex sentence structures. To mitigate translation noise, the framework includes a semantic validation step to ensure that idiomatic expressions and cultural nuances in Tamil are retained during the English translation phase. Fig. 2 outlines the workflow for the translation and reverse translation processes, emphasizing steps to handle idiomatic expressions and semantic nuances. For example, culturally specific phrases like 'அதிகாலை' (early morning) are mapped to contextually appropriate equivalents in English, ensuring retention of meaning during translation and reverse translation. Table 4 summarizes research papers that focus on the translation process for low-resource languages, highlighting their methodologies and languages involved.

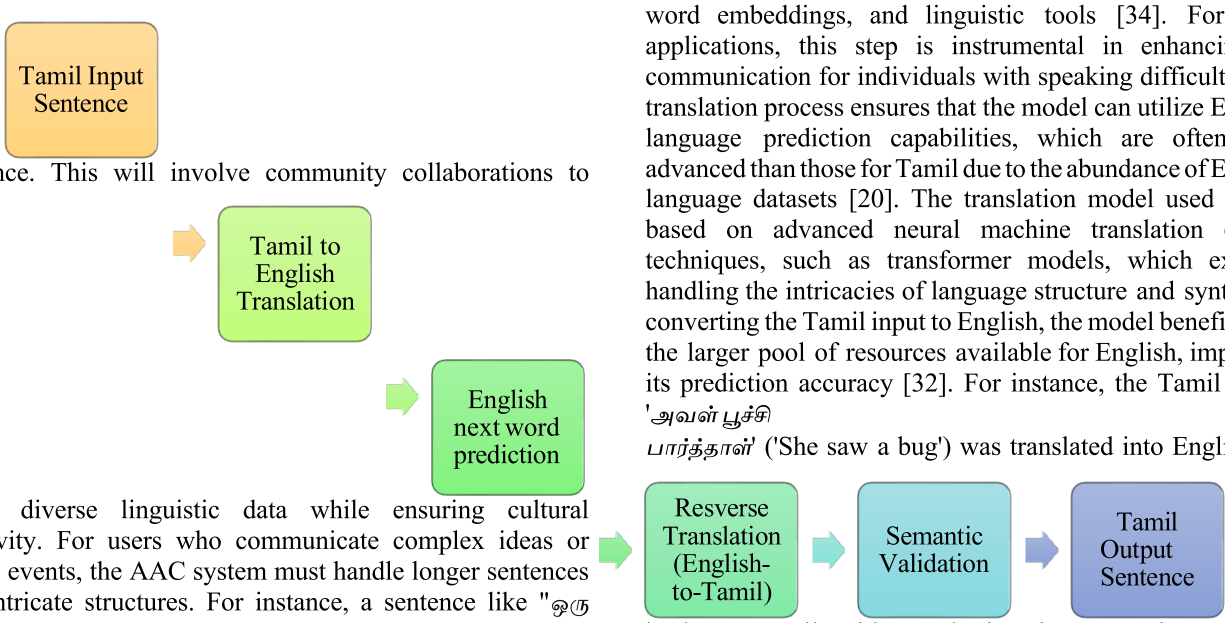


Fig. 2. Translation and Reverse Translation Workflow.

The framework starts by collecting Tamil sentences categorized by length. These are translated into English using Neural Machine Translation (NMT), where the English version is processed for next-word prediction using GRU, LSTM, or BiLSTM models. The final predicted sentence is reverse-translated to Tamil while maintaining semantic integrity. The translation process is implemented using the GoogleTranslator class, which automates the transformation of Tamil sentences into English [36]. The key step in automating the translation of low-resource languages like Tamil to more widely used languages is English [37]. Integration of this step in AAC applications allows the system to tap into the better-resourced English language models for next-word prediction [38]. [39] suggests that this process is helpful for low- resource languages like Tamil, where direct prediction models might be less effective due to the lack of comprehensive datasets. To find the quality of this translation process BLEU Score evaluation metric is used [40]. [41], [42], [43] has employed the BLEU (Bilingual Evaluation Understudy) score metric to evaluate the quality of machine-generated translations against one or more reference translations. Calculating the BLEU score integrates both precision and brevity, accounting for the importance of generating translations that are not only accurate but also appropriately sized relative to reference translations [44].

TABLE 4

THE TRANSLATION PROCESS FOR LOW-RESOURCE LANGUAGES, HIGHLIGHTING THEIR METHODOLOGIES AND LANGUAGES.

Title	Language Focus	Methodology	Published On	Reference
Transfer Learning-Based Neural Machine Translation for Low-Resource Languages	Low-Resource Languages	Transfer Learning, NMT	2023	[45]
OCR Improves Machine Translation for Low-Resource Languages	Various Low-Resource Languages	OCR Integration	2022	[46]
Teaching Unseen Low-Resource Languages to Large Translation Models	Finno-Ugric Languages	Transfer Learning	2022	[47]
Morpheme-Based Neural Machine Translation Models for Low-Resource Fusion Languages	Fusion Languages	Morpheme-Based NMT	2023	[48]
Data augmentation for low-resource neural machine translation	Various Low-Resource Languages	Data Augmentation Methods	2017	[49]
IACS-LRILT: Machine Translation for Low-Resource Indic Languages	Indic Languages (Manipuri, Assamese)	Machine Translation Techniques	2023	[50]
Enhanced back-translation for low resource neural machine translation using self-training	Various Low-Resource Languages	Back-Translation	2021	[51]
Machine Translation for Low-Resource Indic Languages: Challenges and Solutions	Indic Languages	NMT, Back-Translation	2023	[50]
SMaLL-100: Introducing Shallow Multilingual Machine Translation Model for Low-Resource Languages	Low-Resource Languages	Shallow Multilingual NMT model	2022	[52]
Adaptation of Large Multilingual Machine Translation Models to Unseen Low-Reousrce Languages via Vocabulary Substitution	Various Low-Resource Languages	Vo		

D. Next Word Prediction Process

Next-word prediction has become a fundamental feature in AAC applications, as this enhances the communication for individuals with speaking difficulties. This feature allows users to input text more quickly and efficiently by predicting the next word they intend to use, thereby reducing the overall time and effort required to communicate [54]. [55] suggest that the predictive text capabilities can significantly increase the efficiency of communication, as users are more likely to complete their thoughts without interruption. There are few models that help in next word prediction such as Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), and Gated Recurrent Unit (GRU) under Recurrent Neural Network (RNN) and BERT, GPT under Transformers. Transformer-based models such as GPT were excluded from this evaluation due to their primary design for broader contextual understanding rather than sequential next-word prediction, a key requirement for AAC systems. Table 5 summarizes the research papers that focus on next word prediction in Indian languages using RNN and transformer models.

TABLE 5

THE RESEARCH PAPERS THAT FOCUS ON NEXT WORD PREDICTION IN INDIAN LANGUAGES USING RNN AND TRANSFORMER MODELS.

Title	Language	Model Used	Published On	Reference
Next word prediction in Hindi using deep learning techniques	Hindi	RNN	2019	[56]
Exploring Recent NLP Advances for Tamil: Word Vectors and Hybrid Deep Learning Architectures	Tamil	RNN	2024	[57]
Next Word Prediction in Bangla Using Hybrid Approach	Bengali	Transformer	2023	[21]
Hybrid CNN-LSTM Architecture for Bilingual Next-Word Prediction in Punjabi-English Social Media Texts.	Punjabi	RNN, Transformer	2023	[58]
Grapheme to Phoneme Conversion for Malayalam Speech Using Encoder-Decoder Architecture	Malayalam	Bidirectional LSTM (RNN)	2022	[59]

Analysis of Neural Machine Translation for English to Hindi using Long Short-Term Memory Model and Transformer Model	Hindi	Transformer	2024	[60]
Decoding Named Entities: Analysing Hindi–English Code-Mixed Social Media Text	Hindi-English	RNN	2024	[61]
Transformer-Based Word Association of Marathi Text	Marathi	RNN, Transformer	2023	[62]
Hate Speech and Offensive Content Detection in Indo-Aryan Languages: A Battle of LSTM and Transformers	Gujarati	Transformer	2023	[63]

By integrating the advanced next-word prediction models into AAC systems, users benefit from context- aware and efficient communication tools.

E. Reverse Translation Process

The final step in the framework is to translate the predicted English sentence back into low resource languages like Tamil. This step ensures that the output remains in the user's native language, making the communication process seamless and accessible [51]. During this process, the reverse translation model ensures that the predicted English output is accurately mapped back to Tamil, considering nuances and idiomatic expressions in both languages. This step also addresses any ambiguities that might arise during the translation and prediction phases [50]. Reverse translation ensures that the entire process stays within the bilingual framework, enabling the system to provide predictions that are both contextually relevant and linguistically accurate in Tamil [32]. Reverse translation errors, such as the misinterpretation of tense or idiomatic phrases, were minimized using semantic validation techniques, which cross-verify outputs against a reference dataset. This step eases issues like translation errors or misinterpretations that can arise during the first translation phase, making the final output more natural and usable for Tamil-speaking users.

By integrating data collection, translation, next-word prediction, and reverse translation, the bilingual framework ensures that the model can handle a variety of sentence lengths and complexities while utilizing the strengths of both Tamil and English. Categorizing sentences by length improves the model's ability to predict accurately in various contexts, making it a highly adaptable solution for next-word prediction in low- resource languages like Tamil.

4. Results and Discussion

This section presents the results obtained from the translation process and next-word prediction analysis. Tables 6, 7, 8, 9 and 10, along with Fig. 3, comprehensively evaluate the BLEU scores, model performance across varying sentence lengths, and comparisons between LSTM, BiLSTM, and GRU architectures.

Table 6 presents the translation process results. The BLEU score evaluation shows some notable variations across different sentence lengths. The BLEU (Bilingual Evaluation Understudy) score is commonly used to evaluate the quality of machine-generated translations by comparing them to human references. It ranges from 0 to 1, with a higher score indicating better translation quality. In the context of next-word prediction, BLEU score variations across different sentence lengths can offer insights into the model's performance in handling short, medium, and long sentences. Fig. 3 depicts the BLEU score across various sentence lengths. Shorter sentences (<5 words) score higher (0.75) due to their simpler structures and fewer tokens, which reduce ambiguity during translation. Medium-length sentences (6–10 words) face challenges in capturing nuanced relationships, reflected in a lower BLEU score (0.72). Longer sentences (>10 words) achieve a BLEU score of 0.73, benefiting from richer context but facing complexity-related errors.

Table 6.
Results of the Translation Quality

S.No.	Lenth of the Sentence	BLEU Score
1	Less than 5-word sentences	0.75
2	6 – 10 word Sentences	0.72
3	More than 10 Word Sentences	0.73

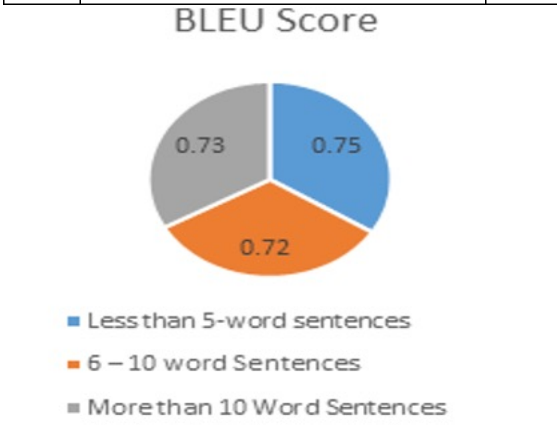


Fig. 3. BLEU scores across sentence lengths

Table 7 presents BLEU Score and Model Performance Across Sentence Lengths. Sentences with less than 5 words achieve the highest BLEU score of 0.75, indicating that the model performs best on short sentences. These BLEU scores validate the framework's ability to retain contextual accuracy during translation, which is critical for AAC applications where effective communication depends on accurate predictions. These scores indicate that shorter sentences are more likely to result in accurate predictions, making the framework particularly useful for AAC users who rely on quick, concise communication. This is likely due to their simpler structures and fewer tokens, which reduce the complexity of predicting the next word. The sentences ranging from 6 to 10 words show the lowest BLEU score at 0.72. This suggests that medium-length sentences may introduce moderate complexity like less predictable word relationships, making prediction more challenging. Sentences with more than 10 words perform slightly better than the medium-length category, scoring 0.73, but still fall below the shorter sentences. The additional context in longer sentences aids prediction but also increases the likelihood of errors due to more complex syntax and relationships. The BLEU scores remain consistent across the sentence lengths, ranging from 0.72 to 0.75. Table 8 Summarizes the findings from research papers that report BLEU scores in machine translation across various language pairs and methodologies.

TABLE 7

BLEU SCORE AND MODEL PERFORMANCE ACROSS SENTENCE LENGTHS

Sentence Length	BLEU Score	Interpretation
C1 (<5 words)	0.75	The high BLEU score indicates the model's ability to accurately predict the next word with minimal ambiguity and fewer syntactic variations.
C2 (6–10 words)	0.72	The drop in BLEU score reflects the model's difficulty in handling these structures and less predictable word relationships.
C3 (>10 words)	0.73	The BLEU score reflects a slight improvement over medium sentences, though errors may still occur from complex sentence structures.

TABLE 8

THE FINDINGS FROM RESEARCH PAPERS THAT REPORT BLEU SCORES IN MACHINE TRANSLATION ACROSS VARIOUS LANGUAGE PAIRS AND METHODOLOGIES.

Study	Language Pair	BLEU Score	Methodology
[64]	English-French	0.397	Statistical Machine Translation
[65]	English-German	0.445	Neural Machine Translation
[66]	English-Spanish	0.537	Sequence-to-Sequence Learning
[67]	Chinese-English	0.697	Attention-based Neural Machine Translation
[68]	English-Arabic	0.291	Statistical Translation with Neural Networks
[69]	English-Japanese	0.430	Phrase-Based Statistical Machine Translation
[70]	English-Italian	0.710	Hybrid Model (NMT + SMT)
[71]	English-Russian	0.780	Neural Translation with Enhanced Attention
[72]	Arabic-English	0.550	Bidirectional LSTM for Machine Translation

Fig. 3 depicts the performance comparison of LSTM, BiLSTM, and GRU Models across Metrics and Classes of the results that are achieved. This model has been particularly successful in Natural Language Processing tasks. The table presents the accuracy, precision, and recall for three different models (LSTM, BiLSTM, and GRU) across three sentence categories (<5, 6–10, and >10 words). Table 9 presents the results of the next word prediction models. Each models have unique characteristics that impact their performance. Table 10 summarizes various research papers with its accuracy on using various model for next word prediction.

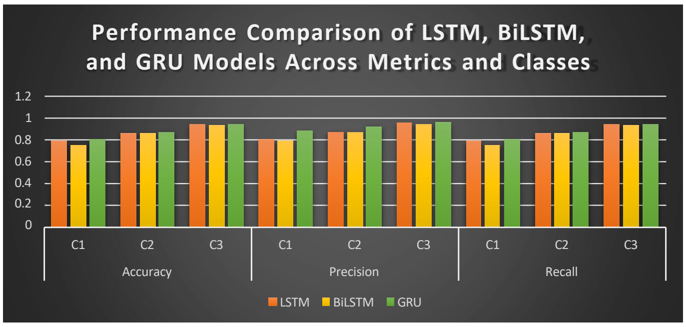


Fig. 4. Performance Comparison of LSTM, BiLSTM, and GRU Models Across Metrics and Classes

TABLE 9

RESULTS OF THE NEXT WORD PREDICTION PROCESS

S.No	Model	Accuracy			Precision			Recall		
		C1	C2	C3	C1	C2	C3	C1	C2	C3
1	LSTM	0.79	0.86	0.94	0.80	0.87	0.95	0.79	0.86	0.94
2	BiLSTM	0.75	0.86	0.93	0.79	0.87	0.94	0.75	0.86	0.93
3	GRU	0.80	0.87	0.94	0.88	0.92	0.96	0.80	0.87	0.94

TABLE 10

SUMMARY OF VARIOUS RESEARCH PAPERS WITH ITS ACCURACY ON USING VARIOUS MODEL FOR NEXT WORD PREDICTION.

Paper Title	Reference	Model Type	Accuracy (%)
Contextual Bangla Next Word Prediction and Sentence Generation Using Bi-directional RNN With Attention	[73]	Bi-LSTM	97.98%
Next Word Prediction in Hindi Using Deep Learning Techniques	[56]	Bi-LSTM	81.07%
Next word prediction using deep learning: A comparative study	[74]	LSTM	75%
Next Word Prediction Using Deep Learning	[75]	LSTM	85%
Prediction-adaptation-correction recurrent neural networks for low-resource language speech recognition	[76]	LSTM	70%

Enhanced Next Word Prediction Using Variational Recurrent Neural Networks	[77]	Variational RNN	88%
Bangla word prediction and sentence completion using GRU: an extended version of RNN on N-gram language model	[78]	Basic RNN	62.5%
Performance evaluation of deep neural networks applied to speech recognition: RNN, LSTM and GRU	[79]	Bi-LSTM	90%
A novel Multi-Layer Attention Framework for visual description prediction using bidirectional LSTM	[80]	Attention-based LSTM	91.5%
Time-aware location prediction by convolutional area-of-interest modeling and memory-augmented attentive LSTM	[81]	Time-Aware RNN	82%

The evaluation of model performance across different sentence lengths highlights distinct strengths and weaknesses among LSTM, BiLSTM, and GRU models. LSTM demonstrates strong and consistent performance across all sentence lengths, with high accuracy (0.79–0.94), precision (0.80–0.95), and recall (0.79–0.94). Notably, its performance improves with longer sentences (>10 words), achieving its best scores in this category. BiLSTM mirrors LSTM's performance, though it slightly underperforms for short sentences (<5 words), with an accuracy and recall of 0.75. However, it maintains comparable performance to LSTM for sentences with 6–10 and >10 words. GRU outperforms both LSTM and BiLSTM for short sentences (<5 words), with the highest accuracy (0.80) and precision (0.88). For longer sentences, GRU matches LSTM's accuracy but slightly lags in precision compared to its performance with shorter sentences.

For sentences under 5 words, GRU is the best performer with the highest accuracy (0.80), precision (0.88), and recall (0.80). In the 6–10 word category, all models perform almost identically, though GRU holds a slight edge in precision (0.92). For sentences exceeding 10 words, all three models achieve nearly identical results, with GRU maintaining a slight precision advantage (0.96). In terms of consistency, LSTM and BiLSTM exhibit stable performance across all sentence lengths, while GRU stands out for its higher precision, indicating fewer false positives. Future evaluations will include user-centric metrics, such as response times and ease of use, through trials with Tamil-speaking AAC users, ensuring practical effectiveness. User feedback on prediction speed, accuracy, and contextual relevance will be crucial to refining the framework further. Metrics such as task completion time and user satisfaction rates will provide additional insights into its real-world applicability. When comparing short and long sentences, all models perform better with longer sentences, likely due to the availability of more contextual information. However, shorter sentences remain more challenging, with GRU showing a clear advantage in handling them. Finally, GRU is the most suitable model for datasets with a higher proportion of short sentences due to its superior precision and accuracy. For mixed or longer sentences (6–10 and >10 words), all three models perform similarly with minor variations. Therefore, GRU is preferred for tasks requiring higher precision, while LSTM is ideal for balanced performance across all metrics. In comparison to traditional AAC tools, the proposed framework significantly improves context retention and next-word prediction accuracy due to the bilingual translation approach. For example, while Avaz relies on pre-set templates and limited Tamil support, our framework dynamically adapts to user inputs using neural prediction models, offering more personalized and accurate predictions. The proposed framework improves next-word prediction by leveraging neural models and bilingual translation. Unlike Avaz, which relies on pre-set templates, this framework dynamically adapts to user inputs, significantly enhancing context retention.

In the comparison of LSTM, BiLSTM, and GRU models across different sentence lengths, BERT is not included primarily due to its fundamentally different architecture and intended use case. While LSTM, BiLSTM, and GRU are recurrent models designed to handle sequential data and are particularly effective for next-word prediction tasks in smaller datasets, BERT operates using a transformer-based architecture, which relies on bidirectional context rather than sequential processing. BERT excels at understanding contextual relationships in entire sentences rather than predicting the next word, making it more suitable for tasks such as language understanding, text classification, and question-answering. Additionally, BERT requires substantial computational resources and a large volume of data for fine-tuning, which may not be practical for small datasets like the one used in this analysis (2030 sentences). The use of autoregressive techniques for next-word prediction is more complex with BERT, often requiring additional architecture adjustments, such as using masked language models or integrating transformers specifically designed for generation tasks (e.g., GPT). Given these considerations, LSTM, BiLSTM, and GRU were chosen for their efficiency in handling smaller datasets and their proven effectiveness in next-word prediction tasks, while BERT's exclusion ensures a focus on models more appropriate for the given dataset size and task complexity. Although BERT was excluded, future iterations will explore fine-tuned transformer-based models like GPT, which may provide superior context understanding while addressing the limitations of sequential models. The framework also prioritizes ethical considerations. To ensure user privacy, differential privacy techniques will be implemented, anonymizing sensitive user data during training. Additionally, fairness metrics will be employed to mitigate biases in predictions, ensuring equitable performance across varying sentence types and dialects. To ensure user privacy, differential privacy techniques like anonymization will be implemented during training. Fairness metrics, such as equal performance across regional dialects (e.g., Kongu Tamil, Madurai Tamil), will be employed to address potential biases. This ensures equitable accessibility for all Tamil-speaking AAC users.

5. Conclusion

This study introduces a bilingual translation framework designed to address the challenge of next-word prediction for Tamil, a low-resource language. The translation models were used to bridge Tamil and English, the framework takes advantage of the extensive resources and pre-trained models available in English. Models such as LSTM, BiLSTM, GRU, and BERT were employed for next-word prediction, showing notable improvements in prediction accuracy. This demonstrates the effectiveness of integrating translation techniques with sequential and transformer models to overcome data scarcity in low resource languages. The proposed bilingual framework is scalable and adaptable, offering a solution for other low-resource languages facing similar challenges. A key contribution of this research lies in its potential application to Augmentative and Alternative Communication (AAC) systems, particularly for users in Tamil speaking community. By enabling accurate bilingual next-word prediction, the framework enhances communication for users in AAC environments, improving the usability and inclusivity of these systems. The framework's ability to balance bilingual translation with next-word prediction offers a template for developing AAC tools that cater to other low-resource languages, fostering broader linguistic inclusivity. This study not only bridges the resource gap for Tamil but also establishes a blueprint for integrating underrepresented languages into AAC systems. Future iterations will incorporate comprehensive real-world testing and adaptive learning features, ensuring the framework evolves to meet diverse user needs effectively. Real-world testing with AAC users will be instrumental in refining the framework. Incorporating adaptive learning mechanisms to personalize next-word prediction based on user behavior is critical for future iterations. This approach empowers the individuals with speaking difficulty by offering more intuitive and contextually relevant suggestions, thus giving a better interaction. The bilingual framework not only addresses the resource gap for Tamil but also sets a precedent for integrating low-resource languages into AAC systems. By incorporating adaptive learning mechanisms and leveraging GPT-based architectures in the future, the framework will evolve to provide more personalized and contextually accurate predictions. Ethical considerations, such as differential privacy and fairness, will remain central to its development, ensuring responsible deployment.

Future work will explore GPT-based architectures to enhance context understanding and prediction accuracy. Additionally, emphasis will be placed on addressing ethical concerns, including data privacy and mitigating model bias, to ensure fair and responsible deployment. A key focus will be on ensuring the ethical use of user data, incorporating differential privacy techniques to safeguard sensitive information, and addressing potential biases in translation outputs to avoid perpetuating stereotypes. Additionally, refining the translation process to preserve semantic integrity and minimize translation noise will further enhance next-word prediction accuracy. Expanding the bilingual corpora and next-word prediction datasets will facilitate more robust model training and evaluation, supporting ongoing advancements in low-resource language processing and AAC technology development. To address ethical concerns, we will employ fairness metrics to evaluate model bias and ensure equal performance across dialects. Privacy safeguards, such as secure data storage and anonymization protocols, will be integrated to protect user information during real-world testing and deployment.

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