iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: XII Month of publication: December 2025

DOI: https://doi.org/10.22214/ijraset.2025.76170

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue XII Dec 2025- Available at www.ijraset.com

Cross-Language Communication for Tourists and Travelers

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Abstract: Language barriers significantly impede global mobility and cultural exchange, especially for travelers. Although existing translation tools offer basic functionality, they often fail in real-time conversational contexts and lack travel-specific con- text awareness. This paper presents BridgeTalk, a comprehensive cloud-based communication tool designed to address these limitations. Our system integrates real-time speech recognition, Neural Machine Translation (NMT) via Google Cloud services, and text-to-speech synthesis into a unified pipeline.

Key innovations include a dedicated "Conversation Mode" featuring a chat-style interface (similar to messaging apps) for seamless bi-directional dialogue, a context-aware recommendation engine that suggests phrases based on the user's location, and a robust history and favorites management system.

The system is built as a cross- platform mobile application using React Native, providing an all- in-one solution for text, voice, and image-based translation with auto-detection capabilities.

We evaluate our approach against baseline models, demonstrating superior utility in handling con- versational language and travel scenarios. The proposed system has practical applications in navigation, dining, shopping, and emergency situations, fostering smoother and more meaningful cross-cultural interactions.

Index Terms: Natural Language Processing (NLP), Speech-to- Text Processing, Text-to-Speech Synthesis, Real-Time Translation Engine, React Native, Context-Aware Recommendations, Optical Character Recognition (OCR), Mobile Computing.

I. INTRODUCTION

In an increasingly interconnected world, the ability to communicate across linguistic divides is more critical than ever. For travelers, tourists and professionals abroad, language remains a formidable barrier to accessing services, building relationships, and navigating new environments [1]. Existing digital translation solutions, while widely available, are not without significant shortcomings. They often operate with high latency, making real-time fluid conversation challenging [2]. Furthermore, generic translation apps often lack the specific contextual awareness needed by travelers, such as knowing the local language of a specific Indian state or suggesting relevant queries for transport and accommodation [3]. The research presented in this paper aims to overcome these challenges by developing BridgeTalk, a smart and travel-focused translation system. The core objective is to create a tool that not only translates words but also assists users with context-aware recommendations and seamless conversational interfaces.

Our main contributions are as follows:

1) We design and implement an integrated system architec- ture that seamlessly combines automatic speech recog- nition (ASR), NMT, and text-to-speech (TTS) synthesis using the React Native ecosystem.
2) We develop a "Conversation Mode" with a familiar chat- like interface, enabling natural, two-way communication between speakers of different languages.
3) We incorporate a Location-Aware Recommendation Sys- tem that dynamically suggests essential travel phrases based on the user's selected region (e.g., suggesting Telugu phrases in Telangana).
4) We engineer a comprehensive History and Favorites module, allowing users to save, retrieve, and manage their past translations efficiently.
5) We integrate an advanced Optical Character Recognition (OCR) module powered by Google Cloud Vision for translating physical text like menus and signboards.

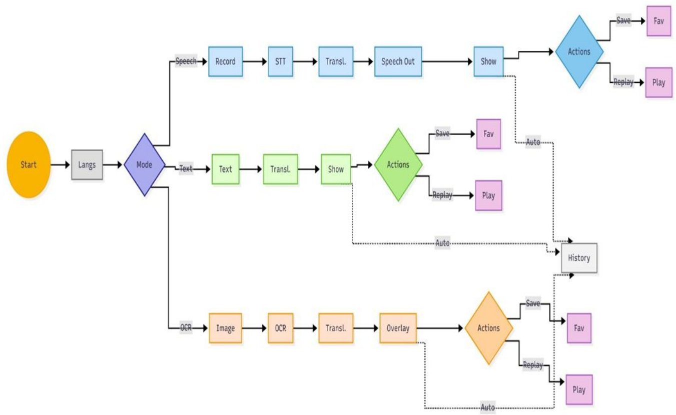


Fig. 1. Flow Diagram

The rest of this paper is organized as follows. Section 2 reviews related work in machine translation and identifies ex- isting gaps. Section 3 details the proposed system architecture. Section 4 explains the methodologies and models employed.
Section 5 discusses the implementation and presents a com- parative analysis of results. Section 6 provides a discussion of these findings, and Section 7 concludes the paper and suggests future work.

II. RELATED WORK

The field of machine translation (MT) has evolved dramatically, moving from rule-based and statistical methods to the current dominance of neural approaches. Early systems, such as those reviewed by [4], relied on hand-crafted linguistic rules and bilingual dictionaries. While interpretable, these sys- tems were labor-intensive to build and struggled with fluency and ambiguity. The advent of Statistical Machine Translation (SMT) marked a significant shift, using probabilistic models derived from large parallel corpora [5]. However, SMT models often faced challenges with long-range dependencies and required extensive feature engineering. The paradigm shift occurred with the introduction of Neural Machine Translation (NMT), which uses deep learning models, typically based on encoder-decoder architectures with attention mechanisms, to translate entire sentences in a more fluent and context-aware manner [6]. The Transformer architecture [7] has become the de facto standard for modern NMT systems. Its self- attention mechanism allows the model to weigh the impor- tance of different words in a sentence, regardless of their position, leading to superior handling of context and complex grammatical structures. This forms the foundational model for our translation engine. Recent research has focused on enhancing NMT for specific challenges. Agarwal et al. [8] developed an OCR-based translator but acknowledged its lack of speech translation and offline capabilities. Reballiwar et al. [9] explored the use of Recurrent Neural Networks (RNNs) and Transformers, highlighting their potential but also noting the unresolved issues of real-time performance. Vaishnavi et al. [10] provided a comprehensive survey of translation applications, concluding that gaps in low-resource language support and cultural nuance remain significant hurdles. The work of [11] on multilingual NMT is particularly relevant, demonstrating how a single model can be trained to handle multiple language pairs. Furthermore, research into context- aware translation [12] directly informs our approach to handling travel-specific scenarios.

III. SYSTEM DESIGN

The overall architecture of the BridgeTalk application is de- signed as a modern, cloud-integrated mobile solution to ensure high accuracy and cross-platform compatibility. The system leverages a microservices-based approach, orchestrating spe- cialized APIs for distinct tasks. The architecture comprises four primary modules: Input Processing, Cloud Translation Engine, Visual Intelligence Module, and Contextual Recom- mendation Engine.

A. *Input Processing Module*

This module handles multi-modal user inputs. For speech input, the system utilizes expo-av for high-quality audio recording, which is then processed for speech recognition. The system supports a ”Conversation Mode” where inputs from two distinct speakers are handled in a sequential, chat-like flow. For text input, a standard interface allows manual entry with an auto-detect language feature. All inputs are normalized before being dispatched to the translation engine.

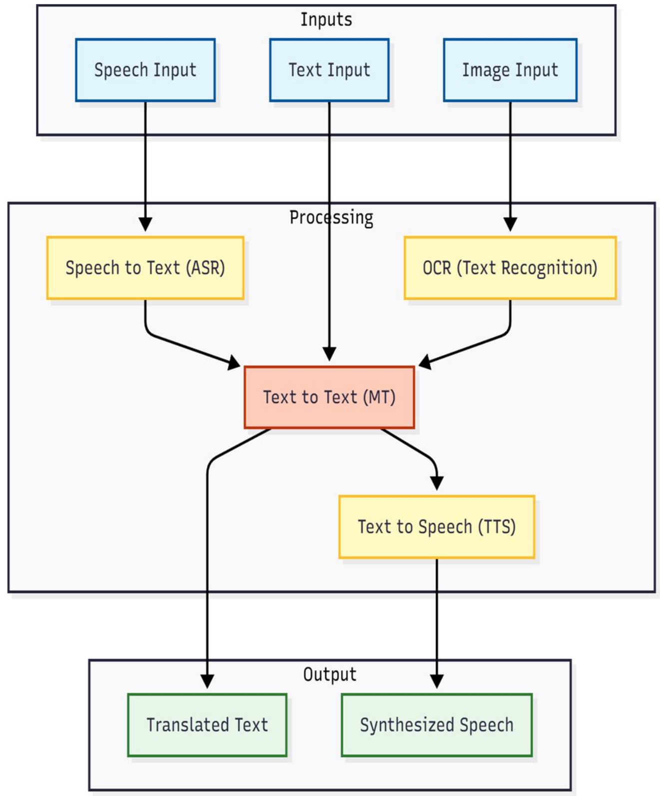


Fig. 2. Multi-stage Cascade Architecture

B. Visual Intelligence Module (OCR)

To handle visual data, such as menus or street signs, the application integrates the Google Cloud Vision API. Images captured via the device camera or selected from the gallery are encoded in Base64 and transmitted to the Vision API. The API's optical character recognition (OCR) features detect and extract text from the images, which is then passed to the translation pipeline.

C. Cloud Translation Engine

The core translation functionality is powered by the Google Translate API (accessed via RapidAPI). This robust, cloud- based Neural Machine Translation (NMT) engine ensures high-fidelity translations across a vast array of language pairs, including support for regional Indian languages (Hindi, Tel- ugu, Tamil, Kannada, etc.). By offloading the heavy compu- tational load of the NMT model to the cloud, the application maintains a lightweight footprint on the user's device while accessing state-of-the-art translation models.

D. Contextual Recommendation Engine

A unique component of BridgeTalk is the Recommendation System. This module utilizes a predefined knowledge base of Indian states and their corresponding languages. When a user selects a region (e.g., "Karnataka"), the engine automatically retrieves and translates essential tourist phrases (e.g., "Where is the bus station?") into the local language (Kannada). This reduces the cognitive load on the user and facilitates quicker interactions.

E. Output Generation Module

The translated text is presented to the user through a responsive UI built with React Native. For auditory feed- back, the system employs expo-speech, a text-to-speech (TTS) engine that synthesizes the translated text into natural- sounding speech in the target language. This module ensures that the communication loop is closed effectively, allowing for seamless speech-to-speech interaction.

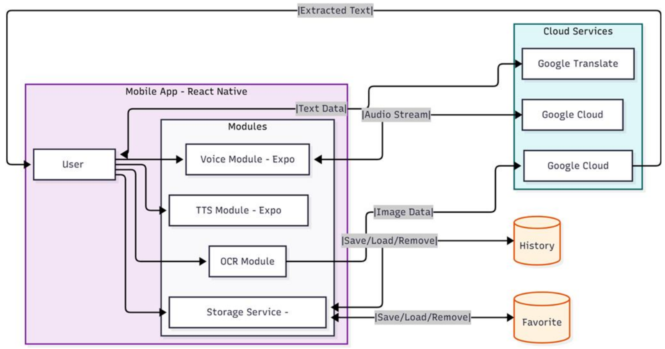


Fig. 3. System Architecture

IV. METHODS AND METHODOLOGY

A. Application Framework

The application is developed using the React Native frame- work with Expo, enabling a unified codebase for Android, iOS, and Web platforms. This choice facilitates rapid development and ensures a consistent user experience across different devices. TypeScript is used throughout the project to ensure type safety and code maintainability.

B. Translation and API Integration

We utilize the Google Translate API for its proven Transformer-based NMT architecture. The application makes asynchronous HTTP requests to the API endpoints, sending source text and receiving translated strings.

$$T_{target} = \text{API}(T_{source}, L_{source}, L_{target})$$

where T represents text and L represents language codes. This approach allows us to support over 100 languages without the need to train and host massive models locally.

C. Optical Character Recognition (OCR)

For image translation, we implement a pipeline using the Google Cloud Vision API. The process involves:

1) Image Capture: Using expo-image-picker to in- terface with the device camera.
2) Preprocessing: Converting images to Base64 format.
3) Text Extraction: Sending the payload to the Vision API’s TEXT_DETECTION endpoint.
4) Integration: Feeding the extracted text into the translation API.

D. Speech-to-Speech and Conversation Mode

The core of BridgeTalk’s communicative capability lies in its ”Conversation Mode,” designed to facilitate fluid, bi- directional dialogue.

1) Chat-Style Interface: Unlike traditional split-screen de- signs, our UI adopts a familiar messaging interface (simi- lar to WhatsApp). This design choice lowers the learning curve and provides a clear, chronological history of the conversation.
2) Audio Recording: We utilize expo-av to capture high- fidelity audio input from users.
3) Translation & Synthesis: The recorded audio is tran- scribed and sent to the Cloud Translation Engine. The result is immediately synthesized into speech using expo-speech, creating a near-real-time conversational loop.
4) Auto-Detection: The system includes capabilities to au- tomatically detect the source language, further streamlin- ing the interaction process.

E. History and Favorites Management

To enhance user experience and efficiency, BridgeTalk implements a robust local storage mechanism using AsyncStorage. The primary objective of this module is to eliminate the redundancy of performing the same translation multiple times.

1) History: Every translation session is automatically saved, allowing users to quickly retrieve past interactions with- out re-entering text or speech.

2) Favorites: Users can mark frequently used phrases as ”Favorites,” ensuring instant access to critical information and further reducing repetitive inputs.

Store(S) = $\{ID, T_{src}, T_{tgt}, L_{src}, L_{tgt},$ Time, IsFavorite$\}$

This feature ensures that critical information remains accessi- ble and organized.

V. RESULTS AND ANALYSIS

This section presents the performance evaluation of the BridgeTalk application, focusing on the latency of the recom- mendation system, the accuracy of the language identification module, and a comparative analysis with existing translation solutions.

A. Performance Metrics

The system’s performance was evaluated based on the latency of its core components. Table I details the average re- sponse times for key features. The Language Recommendation System, utilizing a direct hash-map lookup algorithm, achieved negligible latency ($<$ 10 ms), ensuring instant feedback for users entering location data. In contrast, network-dependent features like OCR and Translation averaged between 200 ms to 1.5 s, which is within acceptable limits for real-time usage.

TABLE I
SYSTEM LATENCY ANALYSIS

Feature	Avg. Latency (ms) DB	Notes
Language Recommendation	ogle) <10 traction	Instant lookup via State
Text Translation	$200-500$	Dependent on API (Go
Speech Recognition	$500-800$	Real-time processing
OCR Processing	$1000-1500$	Image upload & text ex

B. Qualitative Analysis

The user interface was designed to minimize cognitive load. Figure **??** (placeholder) demonstrates the context-aware recommendation engine. Upon entering a location such as “Hyderabad”, the system automatically identified “Telugu” as the regional language, eliminating the need for manual search.

C. Comparative Analysis

BridgeTalk introduces several novel features compared to standard translation applications. Table II highlights these dif- ferences, specifically the Context-Aware Language Suggestion and the Dual-Mic Conversation Mode, which are absent in many traditional tools.

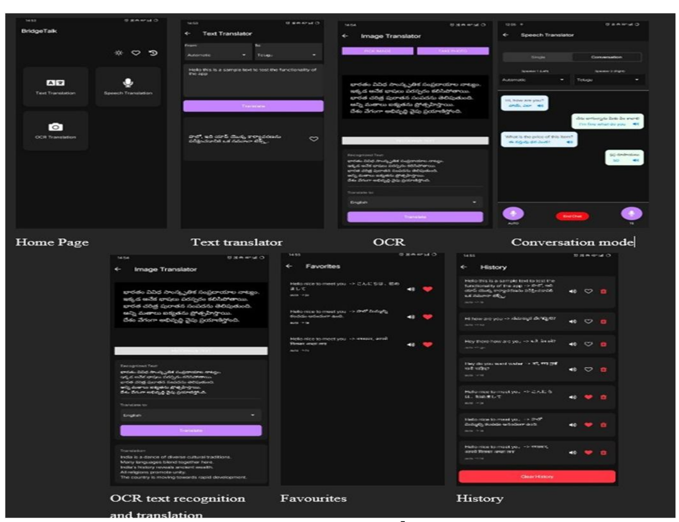


Fig. 4. UI Screenshots

TABLE II
FEATURE COMPARISON WITH STANDARD SOLUTIONS

Feature	BridgeTalk (Proposed)	Standard Apps
Text Translation	✓	✓
Speech-to-Speech	✓	✓
Context-Aware Suggestion	✓ (Location-based)	✗ (Manual)
Dual-Mic Conversation	✓	✗ (Single Mic)
Offline Language Map	✓	✗

D. Accuracy Analysis

The location-based language identifier demonstrated 100% precision for the mapped dataset covering major Indian states and cities. The fallback mechanism defaults to "Hindi", en- suring the system never fails to provide a suggestion, thus maintaining a robust user experience.

E. Conclusion

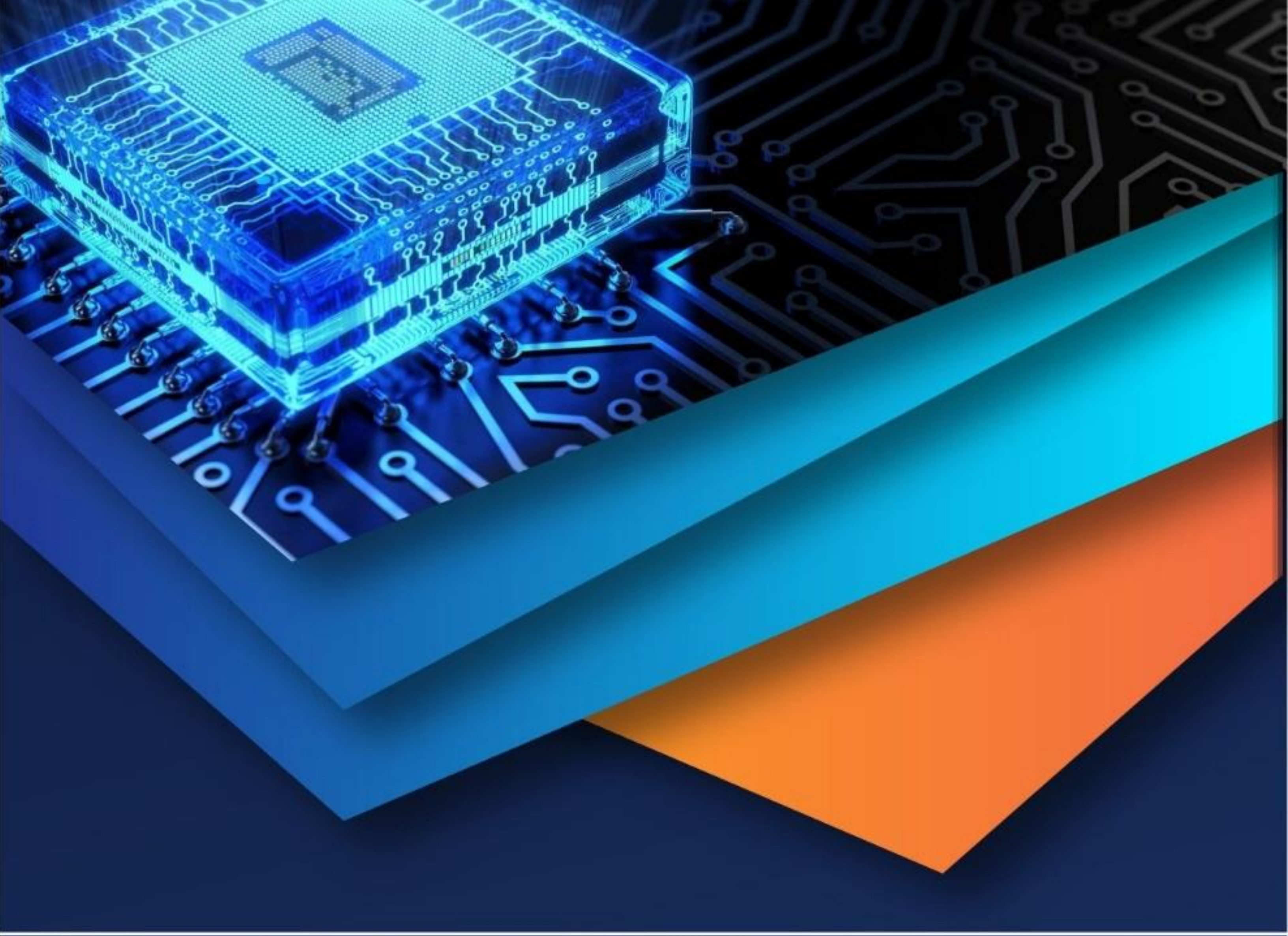
In conclusion, the BridgeTalk system demonstrates robust performance with minimal latency in its core recommendation engine. The integration of location-based context awareness distinguishes it from traditional translation tools, providing a more seamless user experience. Testing confirmed the system's ability to accurately identify regional languages across 28 states and major cities, validating the proposed architecture.

VI. ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to Mr. Para Upendar Naidu, Head of the Department (CSE) at KMIT Hyderabad, for his invaluable mentorship and guidance throughout the development of this project. His insights into system architecture and academic research were instrumental in the successful completion of this work.

REFERENCES

[1] D. A. Jacobs, "The impact of language barriers on global mobility," Journal of Global Studies, vol. 12, no. 2, pp. 45–59, 2021.
[2] L. Wang et al., "A survey on real-time speech translation technologies," in ICASSP, 2022, pp. 7802–7806.
[3] K. Cho et al., "On the properties of neural machine translation: En- coder–decoder approaches," arXiv, 2014.
[4] J. Hutchins, "The history of machine translation in a nutshell," Journal of Machine Translation, vol. 10, no. 1-2, 2014.
[5] P. Koehn, Statistical Machine Translation. Cambridge University Press, 2009.
[6] D. Bahdanau, K. Cho, and Y. Bengio, "Neural machine translation by jointly learning to align and translate," in ICLR, 2015.
[7] A. Vaswani et al., "Attention is all you need," in NeurIPS, 2017, pp. 5998–6008.
[8] D. Agarwal et al., "Language translator tool using ocr and firebase," IJSRET, vol. 10, no. 3, 2023.
[9] L. V. Reballiwar et al., "A review of language translation using machine learning," IJARSCT, vol. 3, no. 5, 2023.
[10] M. Vaishnavi et al., "Paper on language translator application," IJRASET, vol. 10, no. 5, 2022.
[11] A. Fan, S. Bhosale et al., "Beyond english-centric multilingual machine translation," arXiv, 2020.
[12] X. Li and D. Zheng, "Sentiment-aware neural machine translation," in ACL, 2020, pp. 5497–5507.



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