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NLP-reliant Neural Machine Translation techniques used in smart city applications

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ABSTRACT: For smart city applications, Neural Machine Translation (NMT) methods based on Natural Language Processing (NLP) are crucial as they facilitate information sharing and communication among diverse populations. NLP techniques are used in many domains related to smart cities, such as development and research, business, industries, media, healthcare, and residences and communities. The majority of people in India communicate using their regional languages. The majority of applications used by users in smart cities will mostly accept English as input. These people will be able to interact with these smart city devices in their native tongues more effectively with the help of effective machine translation. Just 10% of Indians use English as their primary language of communication; there are 22 official regional languages in India. So, there is a requirement for better machine translation using natural language processing (NLP). Natural language processing for Indian regional languages has a very long way to go until it surpasses the abilities of existing rich NLP applications and techniques for the English language. Machine Translation is a technique of Natural Language Processing (NLP) that provides better inter-lingual communication. For low-resourced Indian languages, effective machine translation systems became important for establishing proper communication. Machine transliteration is a technique to convert source language into target language using a machine. The developed system takes the English language as input and then applies machine translation techniques to translate the source language into multiple languages using a trained RNN model and a multilingual search model that search the input word across all the datasets and generate the output into other Indian languages such as Hindi and Tamil. Our approach achieves top performance for the English-Hindi language pair and comparable results for other cases.

KEYWORDS: NLP; Recurrent Neural Network (RNN); Neural Machine Translation (NMT)

1. Introduction

Various ILNMT architectures for various Indian languages, such as Hindi, Kannada, Tamil (HRLs), Marathi (LRLs), Nepali (ZRLs), and Sinhala, were covered by many researchers. An MNMT system was presented by researchers to overcome the problems associated with low-resource language

translation. This model consists of two MNMT systems: one-to-many for English-Indic and one-to-many for Indic-English. Each system has a shared encoder-decoder that has thirty translation directions and fifteen language pairs. In smart cities, effective multilingual communication is required. In order to facilitate communication between multilingual locals, visitors, and city officials, NMT offers real-time translation services. Smoother interactions in domains like emergency response, transportation, and public services are made possible by this. Initially, the machine transliteration approaches were mainly based on traditional and statistical methods. But, after the emergence of deep learning techniques, researchers are adopting these approaches for machine transliteration. Over the years, various rule-based approaches and Named Entity Recognition (NER) approaches have been used for multilingual translation using the phonetics of source and target. These multilingual translation approaches were mostly statistical and language-specific. In view of various Indian regional languages, there exists the immense need for machine multilingual transliteration.

The existing machine transliteration systems have various challenges, such as pronunciation varies across multiple languages and different dialects of the same language, different structures of different languages, missing of common delimiters in a few languages, translation ambiguity of regional language words, usage of homograph words for which the meaning of the word changes with the change in context, existence of multiple scripts in a few languages such as Punjabi, Gurmukhi, etc., use of multiple languages in a sentence, automatic POS tagging based on sentence grammatical structure. These challenges make the multilingual translation very difficult. So, there is a huge demand for effective approaches to overcome the above-discussed challenges and to improve existing models. According to literature, various machine learning techniques have been utilized for this task, such as the direct MT system, which is based on dictionary lookup, the statistical MT system based on corpus and statistical models, the interlingua-based system based on universal natural language, and the and the knowledge-based MT system, which is based on deep learning and whose core is neural networks.

The system proposed in many research papers works on some of these challenges and enhances the performance accuracy of the machine-translated text. There are various types of machine learning systems designed using traditional algorithms over the years, which are also highlighted in the research work. Many different neural network models and architectures have been developed in the last few years.

Literature has revealed that various neural network architectures have been developed to improve machine translation accuracy. But Neural Machine Translation (NMT) requires a huge dataset to learn the patterns or language rules as well as the context of the corpus. There are two types of Neural Machine Translation (NMT) architectures. One is Recurrent Neural Network (RNN) along with LSTM and Neural Machine Translation (ConvS2S NMT) framework used for the machine translation along with experimental methodology and results. Many researchers described the process of how the Indian language can be processed by applying various techniques such as tokenization, pre-processing techniques, machine translation, Recurrent Neural Network (RNN), full-text search using the CLIR model, and final output generation in multiple Indian languages. Many researchers have performed machine translation on the English-Hindi parallel corpus, which compiles all corpuses available in the public domain, including 1.40 million parallel segments consisting of sentences, phrases, and dictionary entries. Machine Translation is one of the key areas of Natural Language Processing (NLP) and helps in breaking the language barrier and in facilitation of inter-lingual communication. With the evolution of information technology, many documents are available in multilingual languages, so the need for effective machine translation systems became important for establishing proper communication. Machine transliteration is a technique to convert source language into target language using a machine.

This paper details the approach and methodology incorporated for the machine transliteration of the source language input text into other Indian languages accurately and unambiguously without changing the phonetics or the pronunciation of the source language text. Initially, the machine transliteration used to be done using traditional and statistical methods. With the emergence of deep learning techniques, few research attempts have been made using deep learning. Over the years, various rule-based approaches and Named Entity Recognition (NER) have been used for multilingual translation based on the phonetics of source and target languages using statistical and language-specific methods. In the presence of various Indian regional languages, the immense need for machine multilingual transliteration has emerged.

The existing machine transliteration systems had various challenges such as pronunciation varies across multiple languages and different dialects of the same language, different structure of different languages, missing of common delimiters in few languages, translation ambiguity of regional language words, usage of homograph words for which the meaning of the word changes with the change in context, existence of multiple scripts in few languages such as Punjabi has Gurmukhi, etc., use of multiple languages in a sentence, automatic POS tagging based on sentence grammatical structure, straightway comparison not possible due to wide variation in language pairs, missing sounds, etc. The system proposed in this research paper works on some of these challenges and enhances the performance accuracy of the machine-translated text. There are various types of machine learning systems designed over the years, which are also highlighted in the research. Direct MT system, which is based on Dictionary Lookup; Statistical MT system based on corpus and statistical models; interlingua-based system based on universal natural language; knowledge-based MT system, which is based on artificial intelligence; and deep-learning-based systems based on machine learning and neural networks.

Neural Machine Translation (NMT) is a new approach to machine translation with significant advantages over traditional approaches in terms of better translation performance and reduced model size. It translates as an end-to-end trainable supervised machine learning problem. The neural network consists of an encoder and decoder network. The encoder extracts a fixed size length of vector representation from a variable length input sentence. The decoder then generates the correct variable-length target translation. The developed system tokenizes the source language text, and then the text is pre-processed using various techniques such as stemming, lemmatization, stop-word removal, etc., and then the machine transliteration process is performed based on the trained NMT models and Seq-2Seq model using segmentation techniques such as character-based or byte-pair-based. After the machine translation of the input text, the text is further searched using a multilingual search engine, which searches the source language words in the target multilingual datasets. The output of the search engine provides the details of the translated word in the target dataset document along with the text position.

2. Literature review

The deep learning-based approach to machine transliteration described by authors Soumyadeep et al.[1] details the two types of Neural Machine Translation (NMT) architectures, namely Recurrent Neural Network (RNN)-based NMT framework and the convolutional sequence-to-sequence Neural Machine Translation (ConvS2S NMT) framework used for the machine translation, along with experimental methodology and results. The authors Harish and Rangan[2] detail the process of how the Indian language can be processed by applying various techniques such as tokenization, pre-processing techniques, machine translation, Recurrent Neural Network (RNN), full-text search using the CLIR model, and final output generation in multiple Indian languages. The authors Kunchukuttan[3] have performed machine translation on the English-Hindi parallel corpus, which compiles all corpus available in the public

domain, including 1.40 million parallel segments consisting of sentences, phrases, and dictionary entries. The corpus was tested on statistical as well as Neural Machine Translation systems. The source text is normalized using 'Moses' tokenizer for English and IndicNLP for Hindi and then processed. The NMT setup described in their research work included an RNN-based encoder-decoder architecture containing 512 GRU units each. The NMT system was trained using 'Adam Optimizer' with a learning rate of 0.0001. The system designed by this author uses the direct MT technique, which can convert web-based document languages, along with Babylon translation software and online translation tools PROMT and Google Translator. Also, offline translation tools are briefed in this research work, including Systran, METAL, English to Bangla phrase-based machine translation, Anglabharati, Anuvadaksh, UNL-Based Encovertor-Decovertor, Anusaaraka, Sampark, etc. The authors Vidya et al.[4] have described the approach for cross-lingual information retrieval amongst various languages along with emphasizing the pre- and post-processing strategies for the queries entered in the source language. The system designed uses Google Translator for translating into languages supported by the Google Search Engine. They have described various MT systems in field testing or as web services, such as the 'Anglabharti' project, which was launched for machine translation from English to Hindi; the 'Mantra' MT system, which translates from English to Hindi in specified domains of personal administration, office orders, etc.; the 'Anusaaraka MAT system', which translates Kannada, Bengali, Marathi, Punjabi to Hindi; the 'Shiva & Shakti" MT system, which translates from English to Hindi; and the Universal Networking Language (UNL)-based English-Hindi MT system. The authors Sanjay and Pramod have also briefed on various types of machine translation systems such as Anusaaraka, Mantra, Matra, AnglaBharti, AnuBharti, Shiva and Shakti, Anubaad, and Sampark used for translation of Indian languages. The paper described the literature survey done for transliteration from one language to another using various approaches. The author Narayan[5] has described the machine translation using a combination of rule-based and quantum neural network approaches. The paper describes the quantum neural architecture-based algorithm used for machine translation from English to Hindi. The author Sheshadri[6] has performed experiments on neural machine translation on a Hindi to English parallel corpus. The authors Islam et al.[7] have performed studies on the various applications of NLP developed for North-East languages. Bhattacharyya[8] highlighted Indian languages have diversity, so for Indian languages, proposed solutions must be applicable to multiple languages. Godase and Govilkar[9] focused on different machine translation projects and highlighted the approach and observations in detail. Khan[10] conducted very minute research work toward Urdu transliteration. Mallick et al.[11] verify the efficacy of the proposed approach from the higher BLEU scores achieved as compared to the state of the art for translation tasks on the German-English dataset. Manogaran et al.[12] use deep learning techniques to extract opinions from large datasets. Philip[13] provides and analyses an automated framework to obtain such a corpus for Indian. Ramesh et al.[14] demonstrate MT systems produced via a social media-based human evaluation scheme. Singh and Kumar[15] inspected the word vectors of 66 ambiguous Punjabi nouns for an explicit WSD system of Punjabi language. Srivastava and Govilkar[16] present a survey of paraphrase detection techniques for Indian regional languages. Vathsala and Holi[17] analyses the social media data for code-switching and transliterate it to English using a special kind of RNN. Yu et al.[18] propose a "reread" mechanism to transfer the outputs of the first-pass encoder to the second-pass encoder. Zhou et al.[19] propose a deep neural network-based system combination framework leveraging both minimum Bayes-risk decoding and multi-source NMT.

3. Types of MT systems

There are various types of MT systems that have evolved over the years, as described below:

1) Rule-based Approach MT System—It consists of a collection of grammar rules, a bilingual or multilingual lexicon, a dictionary, and software programs to process the rules.
2) Direct translation approach—it translates direct word to word with the help of a bilingual dictionary.
3) Interlingua-based translation approach—it presents source text into an intermediary (semantic form) called Interlingua, and then further it is translated to target text. The advantage is that the analyzer and parser of source text are independent of the target text generator.
4) Transfer-based translation approach—it performs analysis, transfer, and generation. Firstly, the source language is parsed to produce a syntactic representation of the sentence. Then the results are converted into equivalent target language-oriented representations. Further, a morphological analyzer is used to generate the final translated text.
5) Statistical-based approach—This approach is based on the statistical and knowledge models that are extracted from bilingual or multilingual corpora. The training is done using a supervised/unsupervised statistical machine learning algorithm, which builds statistical tables with information about characteristics of well-formed sentences and correlation between sentences and between languages. Further decoding is done to find the best translation for the input sentences. There are 3 types of statistical-based approaches, namely word-based translation, phrase-based translation, and hierarchical phrase-based model. The best translation is chosen based on the highest probability of the probability distribution function represented as p(e | f).

$$e = \text{argmax}\ p(e|f) = \text{argmax}\ p(f|e)p(e) \quad (1)$$

6) Hybrid-based translation—This combines both rule-based and statistical-based approaches. This approach utilizes some rules for pre-processing the input data as well as post-processing the output generated.
7) Knowledge-based translation—This required complete understanding of the source text prior to translation into the target text. It is implemented on interlingua architecture. The system needs to be supported on lingual semantic knowledge about meanings of words and combinations.
8) Example-based translation—This approach reuses the examples of already existing translations. This involves translation by analogy and is trained on a prior knowledge base of bilingual corpus.

4. Proposed methodology

The raw input text of the source language may be in structured/unstructured form. There are various language processing techniques, including pre-processing of texts and machine translation of texts using neural machine translation, that are applied to translate the source language into target Indian languages (**Figure 1**).

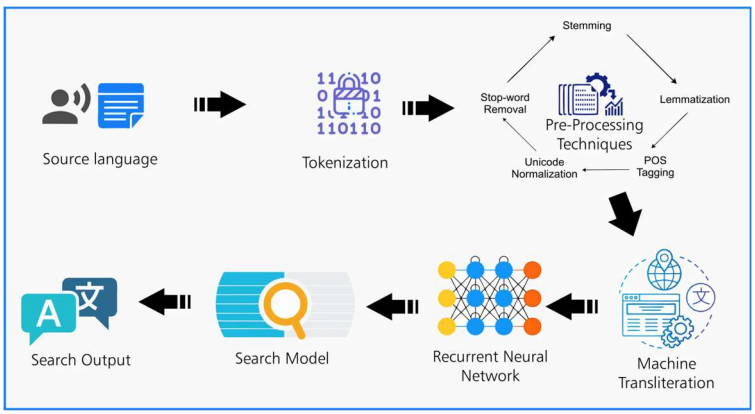

Figure 1. Language processing.

The methodology used for multilingual machine translation and language processing is described as below:

Step 1: Tokenization: The input source language serves as a raw text that is tokenized into lexical/basic units at the word or sentence level in text processing applications. The lexical/basic units are termed as tokens. The sentence-level tokenization is used for detection of the sentences based on sentence ending and boundary ambiguity, and the word-level tokenization is used for tokenization of all the sets of words in the whole document, which serves as a lexical unit.

Step 2: Pre-processing techniques: The source language input text is further processed using various pre-processing techniques such as stemming, stop-word removal, lemmatization, POS tagging, Unicode normalization, etc.

Step 3: Neural network: Recurrent Neural Network (RNN)-based Neural Machine Translation (NMT) is used for transliteration of language from the source language to various Indian languages. This is a sequence-to-sequence-based model that helps in machine translation and text summarization considering the context of the source language.

The RNN neural network consists of hidden states h and optional output y, which operate on a variable length sequence $x = (x_1, x_2, \ldots, x_T)$. At each time step, t, hidden state h_t of the RNN is updated by

$$H_t = f(h_{t-1}, x_t)$$

RNN is a natural generalization of feedforward neural networks to sequences. Given a sequence of inputs $(x1, \ldots, xT)$ a standard RNN computes a sequence of outputs $(y1, \ldots, yT)$ by iterating the following equation:

$$h_t = sigm(W^{hx}x_t + W^{hh}h_{t-1})$$

$$y_t = W^{yh}h_t$$

RNN can easily map sequences to sequences when the alignment between inputs is known ahead of time. The RNN encoder-decoder framework is the best technique used for the training of the model. The encoder converts the source sentence into vectors, which hold the meaning of the sentence, and further, the vectors are processed by the decoders to generate translation output. The RNN model consists of multi-layers along with Long Short-Term Memory (LSTM), which captures long dependency such as syntax structure and Gated Recurrent Unit (GRU). The LSTM predicts the next words of the target sequence given the previously translated words from the sequence. The bi-directional LSTM and BLEU metric are used for evaluation.

Step 4: Search engine model: A cross-lingual information retrieval (CLIR) model is used that performs multilingual text mining for cross-lingual text retrieval. The CLIR model helps in the retrieval of the relevant information from the document collection written in different languages. CLIR searches for the relevant term/word in other document datasets. Query translation is performed based on a corpus-based method using a parallel corpus having a set of identical texts written in multiple languages. CLIR and multi-lingual text mining approaches analyze the multi-lingual textual data employing techniques from information retrieval, NLP, and machine learning.

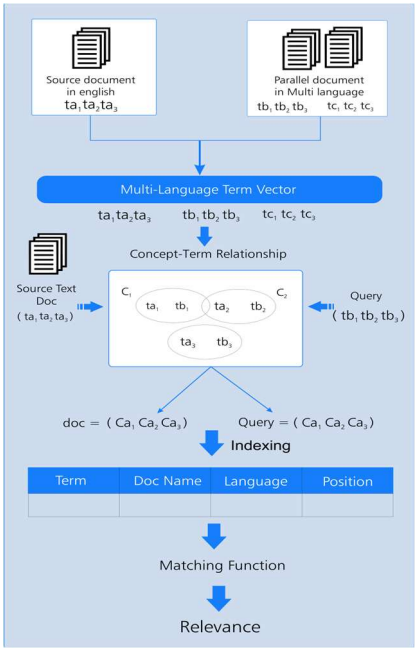

Figure 2. Search engine model.

As described in **Figure 2** above, the terms present in the source document in English and terms present in parallel multi-language documents such as Hindi and Tamil are identified, and a multi-language term vector is created. Further, the multilingual concept-term relationship is identified among the multilingual terms of the source document with the parallel multilingual documents from the parallel corpus. The modified CLIR model proposed in this paper searches the input term/word in English with the multilingual document datasets. Based on the concept-term relationship, the terms are indexed, and details about the term/word, document name, language type, and position of the term/word in the document are captured for further matching the correct word using a search model based on the term relevance.

Step 5: Multi-lingual search output: The source language is converted to multi-lingual languages after processing through the RNN model and incorporating various machine transliteration techniques.

5. Experimental setup

The developed multilingual translation system is based on deep learning-based algorithms such as Neural Machine Translation (NMT)-based Recurrent Neural Network (RNN) for translation of the source language into other multilingual Indian languages. The source language text is tokenized, preprocessed, and matched with the trained machine transliteration-based RNN model. Thereafter, a multilingual search is performed to identify the multilingual word position in the target document and share the results.

Some of the Python libraries that are used for the development of the model include langdetect, textblob, Englishtohindi, indicnlp, indicscripts, phonetic_sim, indic_normalize, and English_script. Indic_tokenize, indic_detokenize, sentence_tokenize, sinhala_transliterator, Unicode_transliterate, acronym_transliterator, script_unifier.

6. Experimental results and analysis

The proposed multilingual translation model is evaluated based on the following performance

metrics: accuracy, precision, recall, and F1-score. The developed system is tested on a dataset size of more than 49 million sentence pairs consisting of multilingual documents in various Indian languages. The below table, named **Table 1**, summarized the results obtained with the developed multi-lingual translation model for conversion of different language pairs from source language to target Indian language: The largest parallel corpus collection of Indic languages, including Assamese, Bengali, Gujarati, Hindi, Kannada, Malayalam, Marathi, Oriya, Punjabi, Tamil, and Telugu, is available to the public via Samanantar.

Dataset analysis in terms of words/stop-words/unique words.

Table 1. Details the statistics (https://ai4bharat.iitm.ac.in/samanantar/).

Sr. No	Parallel corpora	Words	Lines
1	English-Bengali	9,80,12,782-8,61,96,471	84,35,356-84,35,356
2	English-Punjabi	17,17,791-13,79,148	1,38,354-1,38,354
3	English-Tamil	3,07,76,956-2,84,91,118	30,19,564-30,19,564

The above table, named **Table 2**, presents performance metrics for a machine translation system across different language pairs. Each row corresponds to a specific language pair, and the columns provide various evaluation metrics, including accuracy, precision, recall, and F1 score. As per the results obtained, it is observed that the accuracy, precision, recall, and F1-scores are better for multi-lingual translation of English to Hindi compared to translation to other Indian languages such as Tamil, Bengali, and Punjabi. The efficiency can further be increased by an increase in the size of the dataset. English-Hindi language pair size is 3.21 GB. So, it achieves top performance for the English-Hindi language pair and comparable results for other cases.

Table 2. Performance accuracy calculations.

Sr. No.	Language pairs	Accuracy	Precision	Recall	F1-score
1	English-Bengali	85%	74%	78%	74%
2	English-Punjabi	75%	70%	88%	70%
2	English-Tamil	70%	66%	62%	66%

7. Conclusion and future work

This paper describes the methodology used for language transliteration from the source English language to other regional languages (Tamil, Bengali, Punjabi, etc.) using machine transliteration techniques, the RNN model, and a multilingual search processing model.

This system currently supports the information retrieval related to three languages, namely English, Hindi, and Tamil. In the future, the developed system shall support language translation for other major Indian regional languages such as Bengali, Telugu, Gujarati, Urdu, Kannada, Punjabi, and Marathi. Along with this, further efficiency shall be enhanced by the developed system.

For Indic languages primarily, the shift of MT from the SMT platform to the NMT platform represents a paradigm shift in NLP research. NMT models continue to have an insatiable appetite for data despite their progress, and recent findings on low- and zero-resource languages indicate that there is still more work to be done.

Author contributions

Conceptualization, RKD and OP; methodology, RKD; software, RKD; validation, PN, OP and RKD; formal analysis, RKD; investigation, RKD; resources, RKD; data curation, RKD; writing—original draft preparation, OP; writing—review and editing, OP; visualization, OP; supervision, PN; project administration, PN; funding acquisition, RKD. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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