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Cross-Lingual Short-Text Semantic Similarity for Kannada–English Language Pair

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Abstract: Analyzing the semantic similarity of cross-lingual texts is a crucial part of natural language processing (NLP). The computation of semantic similarity is essential for a variety of tasks such as evaluating machine translation systems, quality checking human translation, information retrieval, plagiarism checks, etc. In this paper, we propose a method for measuring the semantic similarity of Kannada–English sentence pairs that uses embedding space alignment, lexical decomposition, word order, and a convolutional neural network. The proposed method achieves a maximum correlation of 83% with human annotations. Experiments on semantic matching and retrieval tasks resulted in promising results in terms of precision and recall.

Keywords: sentence similarity; word embedding; Kannada monolingual embedding; short-text semantic similarity; lexical decomposition; cross-lingual semantic similarity

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1. Introduction

The fundamental and difficult task in the field of natural language processing is determining the semantic similarity between two sentences. In the past several years, a significant amount of textual data have been produced and made available via websites, online news articles, etc. So, there is a need to design an effective method to calculate the semantic similarity between text data present in the given input documents. It has applications in many NLP domains, including text summarization, information retrieval, text categorization, machine translation, question-answering systems, and webpage retrieval.

For the calculation of semantic similarity, early methods used techniques like Term Frequency–Inverse Document Frequency (TF-IDF), Bag of Words (BoW), etc., to describe text data. However, certain words have many meanings depending on the context, and the same notion may be expressed by a different collection of words; therefore, these strategies may fail. Think about the phrases "Tony and Peter studied math and physics" and "Tony studied math and Peter studied physics" for instance. Despite the fact that these two sentences contain the exact same words, their meanings are completely different. The two sentences "John loves athletics" and "John is fond of sports" have a similar structure but use different terms to communicate the same idea. The older approaches thus ignore the semantic characteristics of the text and only capture its lexical features. Semantic-based similarity approaches have been suggested as a way to get around these restrictions. Semantic textual similarity (STS) measures the semantic relationship between text data by computing a rank or percentage of similarity between texts.

Estimating the semantic similarity between two sentences in various languages is the basic goal of cross-lingual semantic textual-similarity systems. This is a difficult challenge in natural language processing as well because it compares things like topics, emotions, and opinions [1–4]. In this work, we propose a method to calculate cross-lingual semantic similarity for the Kannada language, which is spoken by more than 60 million people in the southern Indian state of Karnataka. Moreover, the All India Council for Technical Education (AICTE) has started the process of translating educational course materials and textbooks into many Indian languages, including Kannada. As a result, India has a huge market for cross-lingual semantic-similarity systems. Figure 1 illustrates an instance of a cross-lingual semantic-similarity calculation in a practical application. In this scenario, a module designed for cross-lingual semantic similarity assesses the similarity between an English answer key and a Kannada response. This approach can streamline answer paper evaluation, especially in multilingual countries where responses are often written in local languages. Assuming digitized and accessible responses, the module's score can feed into a decision system. India, with its over 22 official languages, has increasingly promoted local language use in education and exams. While questions are often provided in English and other local languages, responses can be in any language. By comparing the English answer key to the local language response, semantic similarity can be assessed. This method holds potential for machine translation evaluation and automatic grading. The following are the main contributions of the proposed research work:

- We provide a method for computing the semantic textual similarity (STS) between sentences in Kannada and English that utilizes lexical decomposition, embedding space alignment, and convolutional neural networks. To the best of our knowledge, this is the first attempt to measure STS for the Kannada–English language pair.
- We assess the proposed method's performance in terms of precision and correlation with the human-annotated scores, as well as word-level alignment in the embedding space.

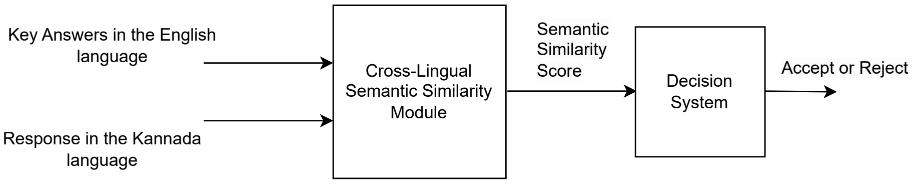

Key Answers in the English language
Response in the Kannada language
Cross-Lingual Semantic Similarity Module
Semantic Similarity Score
Decision System
Accept or Reject

Figure 1. Cross-lingual semantic-similarity calculation in multilingual-answer paper evaluation.

The remaining part of this paper is structured as follows: In Section 2, the related works on semantic-similarity estimation are discussed. The proposed work is presented in Section 3. In Section 4, the experimental results are evaluated and analyzed. Finally, we conclude this paper in Section 5.

2. A Review of Existing Works

It was discovered that there are various methods for determining the semantic similarity of sentences in the literature [5–10]. Three key elements that influence the calculation of semantic similarity were found in [11]. They are word embedding, word weighting measures, and similarity measures. These factors are analyzed using clustering algorithms. In a different strategy [12], the authors looked at lexical, syntactic, and semantic features to identify semantic similarity between phrases in Arabic. To find semantic similarity, machine learning algorithms like linear regression and SVM are used.

To handle uncertainty in the text data, the authors of [13] presented an enhanced approach based on the probabilistic tolerance rough set model. To assess the overall sentence similarity, the approach combines two measures: lower approximation similarity and upper approximation similarity. The authors of [14] proposed a method for determining sentence similarity that is based on a tree kernel and is known as the ACVT kernel. Syntactic data, semantic traits, and an attention-weighting mechanism are all combined. A strategy based on Fuzzy Rough Set was used to calculate sentence similarity in sentences because

Fuzzy Rough Set can handle uncertainty, imprecision, and incompleteness [15]. In another study [16,17], the authors put forth a method for determining text similarity based on word embedding, with an estimation of sentence structure similarity made using graph representations. In order to increase the precision of the sentence-similarity calculation, a mixture of many similarity measurements is employed. Alternatively, in [18], the researchers proposed a technique that leverages word embeddings and external knowledge sources to estimate semantic similarity in short text. In this approach, each short text is represented as two dense vectors. In another work [19], a model for semantic similarity has been proposed based on Optimal Alignment Similarity (OptAlign), Greedy Association Similarity (GrAssoc), and Aggregation Similarity (Aggreg). OptAlign uses optimal word alignment to identify equivalent words across texts. GrAssoc utilizes a greedy algorithm in conjunction with bilingual word embeddings to determine the corresponding words between two text sequences. Aggreg calculates a unified STS score by merging various similarity metrics using an aggregation function. The authors of [20] proposed an embedding-based topic model to effectively identify latent topics from short texts. This approach aggregates the short texts into longer 'pseudo-texts' and then uses a Markov Random Field to infer the topics from the pseudo-texts.

Deep-learning-based models were demonstrated to perform better than other models for NLP tasks [21–24]. A CNN-based approach was employed in [25] to determine the semantic similarity of sentences in medical documents. Recurrent Neural Networks (RNNs) are being commonly employed in Siamese neural networks [26,27] to calculate the degree of similarity between pairs of texts. The recurrent convolutional neural network (RCNN) [28] is another technique used to learn semantic similarity between two sentences. Siamese multilayer CNNs were employed by the authors to extract key information from the input phrases. After combining several representations of the input sentences using a fusion layer, the final similarity score is determined.

To increase the accuracy of their sentence-similarity computation, the authors took a different approach [29] and created a three-layered model made up of (i) a lexical layer, (ii) a syntactic layer, and (iii) a semantic layer. To evaluate the semantic similarity in texts, the authors in [30] developed an attention model made up of word N-grams produced by a bi-directional RNN. In [31], the authors introduced an algorithm that takes into account the similar component and the dissimilar component of every word based on a semantic matching vector and then computes a similarity score in order to address various issues in semantic-similarity computation.

By performing sentence-by-sentence alignment, a different technique was suggested in [32] to determine the semantic textual similarity between sentences. The multiple linear regression method was used to determine an alignment score. SVM, Gaussian Naive Bayes, and KNN classifiers were used via the classification method to conduct multiclass classification. In [33], to conduct a semantic-similarity study between two lines or paragraphs in Bengali, a combination of six statistical parameters, including frequency, matching index, part of speech, entropy, cosine similarity, and sense matching was used. A hybrid strategy was presented in another work [34] by extracting features using the Weighted Fine-tuned BERT algorithm. The Siamese Bi-LSTM network model was used to train the feature vectors. Finally, the similarity scores for each sentence were determined.

Using a deep model built on a bi-directional interaction network, the authors of [35] were able to accurately capture the semantic relationship between sentences. The model combines a deep fusion layer, a deep neural network, and an attention mechanism. Multilayer perceptrons were used for the classification. We may also observe a gated network-based approach [36] for estimating semantic similarity that combines distributed representation and one-hot representation. In [37], the authors introduced the *W-KG2Vec* meta-path-specific model to capture the semantic relationship as well as the text similarity between phrases. Their suggested model BERT-Text2Vec combines an LSTM encoder and a BERT pre-trained model. Along with word-embedding representations, sentiment lexicons and semantic models are also used [38] to detect semantic similarity in texts. In [39], the authors suggested an approach to measure text similarity based on the combination of syntactic and semantic information using knowledge and Corpora. In another work [40], the authors presented KNetwork, an innovative approach for cross-lingual sentiment analysis; this method employs feature vectors derived from translated and transliterated text to enhance accuracy in various linguistic contexts. In [41], the authors introduced a novel approach that combines various features, incorporating two coarse-grained prior-knowledge aspects (sentence sentiment and length), and leverages the XLM-RoBERTa cross-lingual pre-training model. The paper underscores the importance of incorporating both fine-grained and coarse-grained features in sentence-similarity computations to address language-specific biases and enhance overall accuracy. In [42], the authors proposed an approach for the sentiment analysis of Sanskrit texts, addressing the difficulty arising from the limited availability of labeled data for training machine learning models. The methodology relies on zero-shot cross-lingual mapping, enabling sentiment classification in Sanskrit without direct sentiment labels by transferring knowledge from English sentiment labels. In another approach [43], the authors proposed a framework that explains LLMs by analyzing the patterns of communication between neurons within the model. In [44], the researchers developed a GAN-based model, which includes a generative model and a discriminative model, for the purpose of detecting rumors or fake news. In another work [45], the researchers developed a misinformation network model to detect misinformation and fake information during the COVID-19 pandemic.

We observe that several approaches are available for sentence-similarity calculation, and some of the recent approaches can be seen in [46–53]. However, very limited approaches are available in the literature for calculating the semantic similarity between the Kannada and English languages. In this direction, we made an attempt to develop a cross-lingual semantic-similarity approach for Kannada–English sentence pairs. The details of the proposed approach are discussed in Section 3.

3. Methodology

The current short-text semantic similarity (STS) methods find similarity scores between two sentence pairs using word-based or vector-based approaches. The word-based similarity measure uses a lexical database to compute the semantic similarity between a pair of words from two sentences. The semantic equivalency of the word pairings from the two sentences, as well as the alignment of the texts in the two sentences, are used to determine the similarity score. Word embedding, a deep neural network (DNN)-based technique, is used to encode a word into a vector form in a vector-based representation. A big corpus of data was used to train the DNN to produce this vector representation. Thus, the representation can capture word dependencies, context, and semantics. Therefore, combining the two aforementioned strategies would enhance performance. In the proposed research work, we employ a hybrid methodology to investigate the benefits of a word-based methodology and vector-based methodology for computing the cross-lingual short-text semantic similarity on Kannada–English sentence pairs. We go into further detail on word-based similarity and vector-based similarity in the section that follows.

3.1. Word-Based Similarity vs. Vector-Based Similarity

A lexical database similar to WordNet [54–56] can be used to measure the similarity. WordNet is a hierarchical database where the cognitive synonyms (synset) are provided for nouns, verbs, adjectives, and adverbs as separate groups. In most of the existing word-based methods, as a first step, the sentences S and T are subjected to part-of-speech (POS) tagging. In the next step, each word is associated with a sense using *word sense disambiguation* (WSD). This helps to capture the contextual information of words. For example, the word *bank* may have different senses in different contexts. Considering the 'context' of a word helps with the optimal overall similarity calculation. It helps to use WordNet for noun–noun and verb–verb pairs for two words $s_i \in S$ and $t_j \in T$ to obtain the best alignment of words in two sentences. The path length in WordNet between the words and their depth in the tree is considered as the score for alignment [57]. The major advantage of using the word-similarity score with the lexical database is that it provides a mechanism to handle out-of-vocabulary words.

In vector-based representation, normally, a sentence S is represented using a vector $[s_1, s_2, ...s_m]$. In vector-based representation, each word s_i is represented with a pre-trained word embedding. Most of the vector-based methods obtain a similarity score between two short sentences S and T by measuring the similarity between the word pairs (s_i, t_j) in both sentences with the best matching word pairs. However, these methods fail to keep track of the word order and also fail to handle out-of-vocabulary (OOV) words. It is very common to observe OOV words in domain-specific applications. For example, in natural language processing (NLP) applications for healthcare, you are more likely to see common words in a different order that indicate symptoms, signs, diseases, etc. The word order is important to capture the syntactic structure of the sentence. For example, *'Your dog chased my cat'* vs. *'My cat chased your dog'*. The parse trees for these two sentences are not identical. So, it is necessary to consider the word order in sentence-similarity-score computation. The English language follows a strict word order but allows for some freedom at the phrase level [58]. The proposed architecture for semantic-similarity computation is shown in Figure 2. The detailed architecture is shown in Figure 3. The sentence S and sentence T are from two different language pairs. In our case, we perform semantic similarity between Kannada and English short-sentence pairs. As a pre-processing step, we perform tokenization, stopword removal, and word sense disambiguation (WSD). Though the word embedding can capture the context, we apply WSD to English words to enhance the overall performance [59]. The word embedding is carried out as explained in Section 3.2.

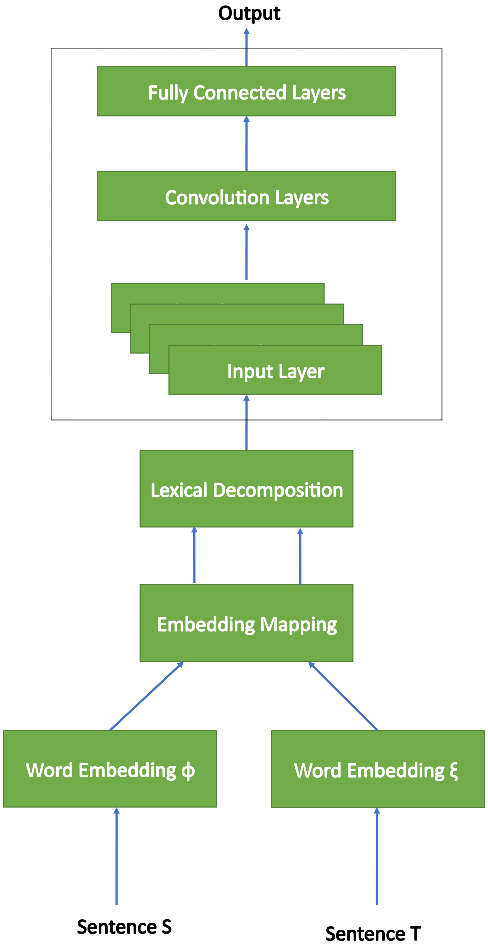


Figure 2. Proposed architecture for semantic-similarity computation.

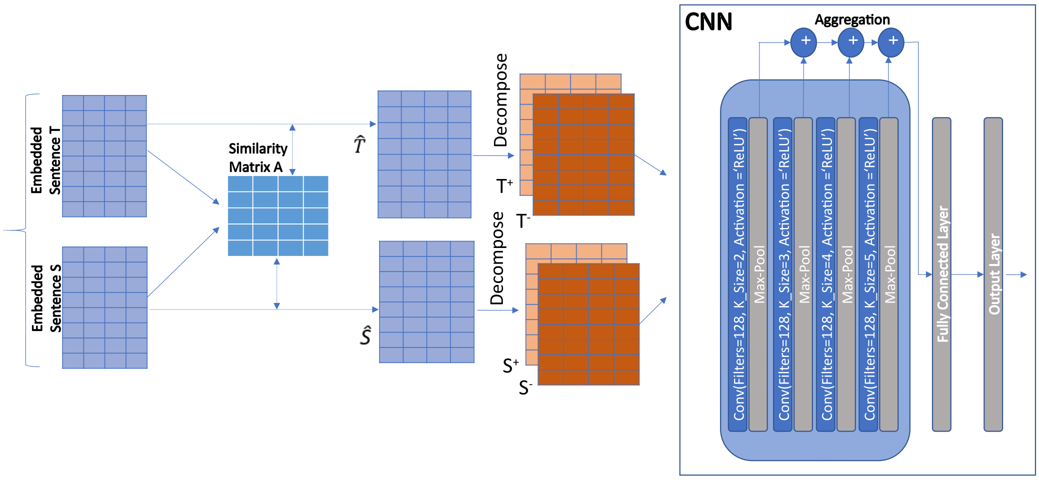

Embedded Sentence T
Embedded Sentence S
Similarity Matrix A
$\hat{T}$
$\hat{S}$
Decompose
Decompose
T+
T-
S+
S-
CNN
Aggregation
+
+
+
Conv(Filters=128, K_Size=2, Activation ='ReLU')
Max-Pool
Conv(Filters=128, K_Size=3, Activation ='ReLU')
Max-Pool
Conv(Filters=128, K_Size=4, Activation ='ReLU')
Max-Pool
Conv(Filters=128, K_Size=5, Activation ='ReLU')
Max-Pool
Fully Connected Layer
Output Layer

Figure 3. A detailed architecture for cross-lingual semantic-similarity computation.

3.2. Word Embedding

We use a word-embedding scheme to create a vector representation of each word appearing in a sentence. In word embedding, a d-dimensional vector is used to represent each word $s_i \in S$ or $t_j \in T$ with a pre-trained neural network [60]. Some of the commonly used embedding schemes are *Word2Vec*, *GloVe*, *FasText*, etc. The *Word2Vec* uses skip-gram or the *Continuous Bag of Word model* (CBOW) for the embedding. A d-dimensional embedding process generates a matrix of dimension $n \times d$ for a sentence with n words. We apply this scheme to both sentences $S = [s_1, s_2, \ldots s_m]$ and $T = [t_1, t_2, \ldots, t_n]$ to obtain the word embedding of both sentences in matrix form. Each s_i and t_j represents the word-embedding vector in d-dimensional space. The pre-trained embedding models can be of two types: (i) the monolingual embedding and (ii) the cross-lingual embedding. In monolingual embedding, the model is trained on a dataset containing text from a single language, whereas in cross-lingual embedding, a dataset containing a parallel corpus with or without word alignment is used to train the model [61]. In our experiment, we explore both monolingual embedding and cross-lingual embedding for sentence representations. The processed texts are embedded into a 300 d vector using pre-trained word-embedding models. The English sentences are embedded using the *tok2vec* model available in Spacy library [62]. Similarly, the Kannada text is embedded using *fasttext* [63]. It uses the skip-gram model with default parameters as described in [64] for Kannada word embedding (the pre-trained word embedding for Kannada is available at https://fasttext.cc/docs/en/pretrained-vectors.html (accessed on 10 June 2024). The method presented in [64] uses a subword representation using character n-grams, thereby enabling the efficient representation of morphologically rich texts.

Monolingual Embedding and Alignment

As we use two different monolingual embeddings for English and Kannada, we perform the alignment of the two embeddings using *VecMap* and MUSE [65–69]. The *VecMap* and MUSE can align the embedding space using supervised or unsupervised methods. The supervised method uses a bilingual dictionary for the alignment. The major concern is the availability of a bilingual dictionary for Kannada–English pairs. The available dictionary has approximately 4 K words, which is inadequate considering the morphologically rich, agglutinative nature of the Kannada language. So, alternatively, we use an unsupervised alignment using the method specified in [70] for creating aligned word embeddings (offline bilingual word vectors, source code available at https://github.com/babylonhealth/fastText_multilingual (accessed on 10 June 2024).

3.3. Lexical Decomposition and Similarity Calculation

From the word embedding stated in the earlier section, we construct a word-similarity matrix denoted by $A_{m\times n}$, where each element a_{ij} is the cosine similarity between the vectors s_i and t_j. The cosine similarity between two vectors is given by

$$cos(\theta) = \frac{s_i \cdot t_j}{|s_i||t_j|}. \tag{1}$$

The range of the cosine similarity varies from -1 to 1. A similarity value of zero indicates that the vectors are orthogonal to each other (highly dissimilar). A value of +1 indicates the highest similarity, and a value of -1 indicates that the vectors are opposite to each other.

This matrix is essential to find the best match for the word (or phrase) s_i in a sentence S with a word (or phrase) t_j in T. The process of finding a match has to be performed for words in both the sentences S and T. This can be formulated as

$$\hat{s_i} = \text{find-match}(s_i, T) = \frac{\sum_{j=0}^{n} a_{ij} * t_j}{\sum_{j=0}^{n} a_{i,j}}. \tag{2}$$

This formulation is similar to the method proposed in [31].

The accuracy of the semantic matching greatly depends on the dimension of the word embedding used and also the word-embedding scheme. The match gives a semantic coverage for the words s_i in T, and similarly for the words t_j in S. We generate the complementary information of semantic coverage by decomposing the vectors s_i and t_j. Here, we consider that the complementary information is represented by an orthogonal vector. So, the decomposition is performed by computing a parallel vector and orthogonal vector termed as *similar components* and *dissimilar components* s_i^+ and s_i^-:

$$\begin{aligned} s_i^+ &= \frac{s_i \cdot \hat{s}_i}{\hat{s}_i \cdot \hat{s}_i}\hat{s}_i \\ s_i^- &= s_i - s_i^+. \end{aligned} \tag{3}$$

Finally, a convolutional neural network (CNN) is used to generate a feature vector for each sentence based on similar and dissimilar components using the convolution operation. The architecture of the CNN is shown in Figure 3. The feature vector is generated using the multiple convolution operation with varying kernel sizes $d \times k$, where d is the embedding dimension and $k = 2, 3, 4, 5$. This operation is analogous to feature extraction using the *n-gram* model. The convolution operations are followed by max-pooling. Finally, the features are aggregated by concatenation. The final layers of the CNN are the fully connected layer and the output layer, which works as the classification head.

3.4. Word-Order Similarity

In the proposed method, we consider word-order similarity to be one of the factors to estimate the semantic similarity of sentences. Given two sentences with a sequence of words, $S = [s_1, s_2, \ldots, s_m]$ and $T = [t_1, t_2, \ldots, t_n]$, we use two strategies to include the word order in sentences. The first method is to compute the word-order similarity using Dynamic Time Warping (DTW) [71]. As DTW describes a distance measure and not a similarity measure of two sentences, we use $d(w_1, w_2) = 1 - sim(w_1, w_2)$ as the distance between two words w_1 and w_2, where $sim(w_1, w_2)$ is the cosine similarity measure of their word embedding. DTW is defined for real numbers, so we use the distance for DTW. The dynamic programming formulation of DTW is given in Equation (4):

$$DTW(S, T) = f(m, n) \tag{4}$$

$$f(m,n) = d(s_i,t_j) + min\begin{cases} f(i-1,j), \\ f(i,j-1), \\ f(i-1,j-1) \end{cases} \tag{5}$$

$$f(0,0) = 0 \quad f(i,0) = f(0,j) = \infty$$

$$where \quad i \in (0,m), \quad j \in (0,n);$$

$$D_\alpha(S,T) = \frac{DTW(S,T)}{length(DTW)}. \tag{6}$$

In Equation (6), $D_\alpha(S,T)$ denotes the word-order similarity score between the sentences S and T. We apply part-of-speech tagging [72,73] to give lesser importance to verbs and adverbs than the nouns and adjectives. We consider the noun, pronoun, and adjective sequences of words denoted by S_p or T_p and the verb, adverb, and other sequences of words denoted by S_q or T_q separately for each sentence. Now, the similarity score considering word order is formed by the weighted sum as given in Equation (7). This helps to handle the structural difference in Kannada–English sentence formation. The proposed vector representation does not consider the function words. Thus, they are removed in the pre-processing stage:

$$D_{wo} = \gamma * D_\alpha(S_p,T_p) + (1-\gamma) * D_\alpha(S_q,T_q). \tag{7}$$

Alternatively, we use positional encoding during the embedding to incorporate the word order. This is similar to the technique of the self-attention mechanism used in transformers [74,75]. The positional encoding (PE) can be summarized using Equation (8):

$$\begin{aligned} PE_{(pos,2*i)} &= \sin(pos/10{,}000^{2i/d_{model}}) \\ PE_{(pos,2*i+1)} &= \cos(pos/10{,}000^{2i/d_{model}}) \end{aligned} \tag{8}$$

where pos represents the position of the word in the sequence and i indicates the dimension. The term d_{model} is the dimension of the word embedding used. The positional encoding is added to the word embedding to obtain the final input vectors.

3.5. Score-Level Fusion

The CNN architecture with minor modifications is used to incorporate DTW-based word-order similarity. The score-level fusion is achieved using an additional node with logistic regression. The inputs to this node are the vector-based similarity score and the word-order similarity. The cost function for this logistic regression is defined in Equation (9). The degree of the regression model used is two:

$$J(\theta) = \frac{1}{2}\sum_{i=1}^{2}[-y_i log(h_\theta(z_i)) - (1-y_i)log(1-h_\theta(z_i))] \tag{9}$$

where the term y_i indicates the expected output for the ith sample and $h_\theta(z_i)$ is the predicted value for the same sample.

4. Experimentation and Results

We use the TensorFlow library for the implementation of the proposed approach. The implemented code is run on an 11th Gen Intel(R), Core-i5, 2.70 GHz Processor with 16 GB RAM and NVIDIA GeForce RTX 3050 GPU having 8 GB memory. Our pre-processing tasks involve steps, like eliminating stop words, tagging parts of speech-disambiguating word senses, and filtering words using WordNet. Our implementation source code is available at https://github.com/muralikrishnasn/Kannada_English_STS (accessed on 10 July 2024). In our experiments, we use the Samanantar Parallel Corpora Dataset [76] to evaluate the performance of the proposed method. The Samanantar Corpora (https://ai4bharat.iitm

.ac.in/samanantar (accessed on 11 June 2024) is available for pairs of sentences in English and 11 Indic languages. The sources of this dataset are the WAT 2021 MultiIndicMT shared task, OPUS, and other sources. The dataset comprises 49.7 M parallel sentences between English and 11 Indic languages, out of which 12.4 M are taken from the existing sources. The remaining 37.4 M sentences are scraped from various online content. This shows that the data used for experimentation are from diverse domains. During dataset preparation, to determine the sentence pair from the scrapped text, the LabSE score is used. Also, a subset of the collected data were manually annotated for semantic sentence similarity (STS) into three classes, namely *definitely accept*, *marginal accept*, and *reject*, as shown in Figure 4. The annotation was performed by sampling 9.566 K English–Indic sentence pairs across 11 Indic languages. The Kannada–English pair has 0.957 K annotated sentences, out of which 70% are used for training and the remaining samples are used for testing.

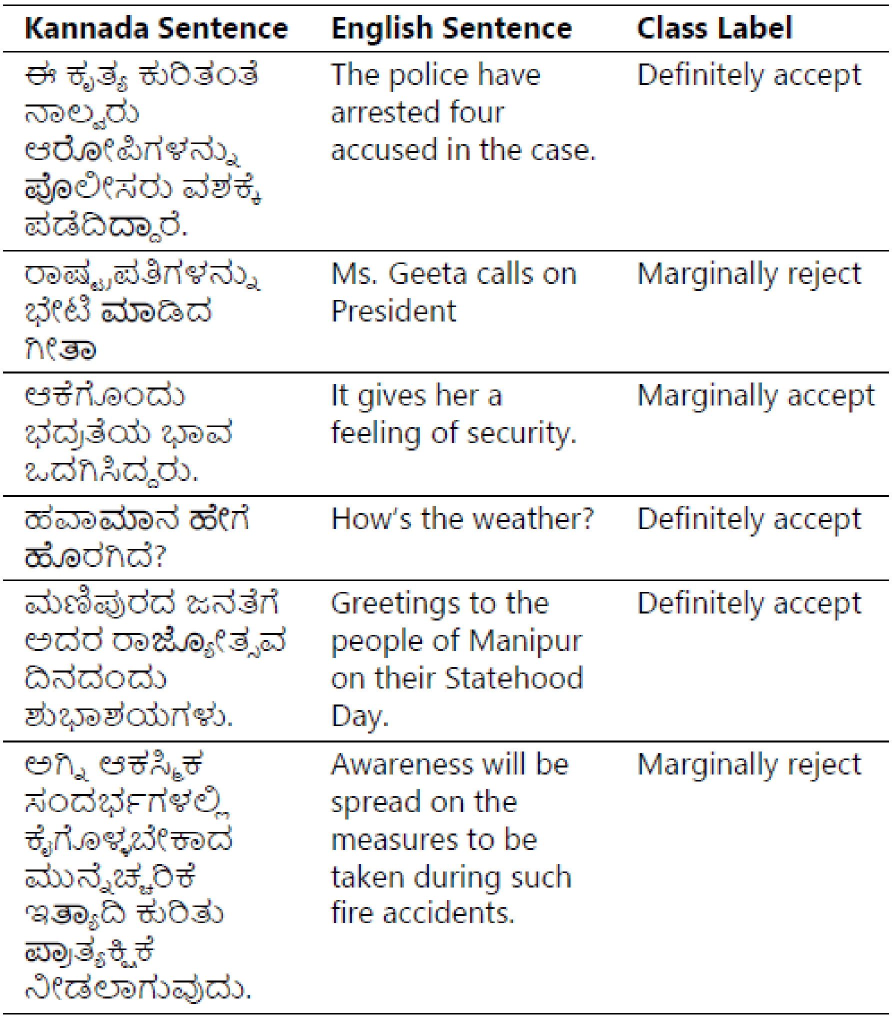
To evaluate the performance of STS and assess embedding alignment, we used a dataset containing human-annotated ground truth and a bilingual dictionary for alignment. We treated embedding alignment as a retrieval task and tabulated the results of retrieving semantically equivalent words from the target language for each source-language word in Table 1. The cosine similarity between their embedding representations is used to measure the precision at different ranks denoted by P@1, P@5, and P@10. Here, P@K represents the K number of words considered to calculate the precision in retrieval. We follow the assessment similar to [19]. We empirically fixed the CNN parameters as follows:

activation function = ReLU,
epochs = 100 ,
learning rate = 0.001,
$\epsilon = 1 \times 10^{-7}$,
loss function = cross-entropy.

Table 1. Assessment of embedding alignment during retrieval at different ranks denoted by @K.

Type of Learning	Alignment Method	Source–Target Pair	P@1	P@5	P@10
Unsupervised	VecMap	KAN - ENG	42.3	72.5	76.2
	MUSE	KAN - ENG	36.9	70.1	78.3
Supervised	VecMap	KAN - ENG	49.6	73.7	80.3
	MUSE	KAN - ENG	47.1	74.3	83.7

No substantial progress has been made in the domain of Kannada–English short-text semantic similarity, making the proposed work one of a kind. We conducted a comparative study using state-of-the-art techniques [19]: *OptAlign*, *GrAssoc*, and *Aggreg*, and the results are presented in Table 2. However, it is evident from the literature that only a few methods have been developed for research on cross-lingual semantic similarity between Kannada and English sentences. The performance of STS at the sentence level is measured in terms of the Spearman correlation coefficient (in % @rank-5) with the human-annotated labels for 4 K sentences. Also, we measure the Mean Reciprocal Rank (MRR) and Mean Average Precision (MAP) to evaluate the retrieval task. Finally, we assess the effectiveness of the proposed method for semantic similarity considering word-embedding alignment with different bilingual dictionary sizes. In Figure 5, we can observe that the word-embedding alignment has no significant improvement beyond the 4 K bilingual dictionary. Also, we conducted a comparative analysis of cross-lingual STS performance on word order using positional embedding and DTW, as shown in Figure 6.



Kannada Sentence	English Sentence	Class Label
ಈ ಕೃತ್ಯ ಕುರಿತಂತೆ ನಾಲ್ವರು ಆರೋಪಿಗಳನ್ನು ಪೊಲೀಸರು ವಶಕ್ಕೆ ಪಡೆದಿದ್ದಾರೆ.	The police have arrested four accused in the case.	Definitely accept
ರಾಷ್ಟ್ರಪತಿಗಳನ್ನು ಭೇಟಿ ಮಾಡಿದ ಗೀತಾ	Ms. Geeta calls on President	Marginally reject
ಆಕೆಗೊಂದು ಭದ್ರತೆಯ ಭಾವ ಒದಗಿಸಿದ್ದರು.	It gives her a feeling of security.	Marginally accept
ಹವಾಮಾನ ಹೇಗೆ ಹೊರಗಿದೆ?	How's the weather?	Definitely accept
ಮಣಿಪುರದ ಜನತೆಗೆ ಅದರ ರಾಜ್ಯೋತ್ಸವ ದಿನದಂದು ಶುಭಾಶಯಗಳು.	Greetings to the people of Manipur on their Statehood Day.	Definitely accept
ಅಗ್ನಿ ಆಕಸ್ಮಿಕ ಸಂದರ್ಭಗಳಲ್ಲಿ ಕೈಗೊಳ್ಳಬೇಕಾದ ಮುನ್ನೆಚ್ಚರಿಕೆ ಇತ್ಯಾದಿ ಕುರಿತು ಪ್ರಾತ್ಯಕ್ಷಿಕೆ ನೀಡಲಾಗುವುದು.	Awareness will be spread on the measures to be taken during such fire accidents.	Marginally reject

Figure 4. A few sample texts from the dataset.

Table 2. Comparative analysis of experimental results with other methods given in [19] on Samanantar Parallel Corpora Dataset [76] using supervised MUSE alignment.

Model	MAP	MRR	Spearman Correlation Coefficient
OptAlign	0.71	0.82	0.75
GrAssoc	0.68	0.64	0.71
Aggreg	0.59	0.62	0.62
Proposed Method	0.81	0.85	0.83

VecMap and MUSE are both powerful tools for cross-lingual word embeddings, but they have different approaches and features. Based on the findings in Tables 1 and 2, it is evident that determining the superiority between VecMap and MUSE is not straightforward. The choice between these methods relies on the specific demands and limitations of our embedding-space-alignment task. Nonetheless, it is worth noting that MUSE demonstrates an improved performance for the KAN-ENG language pair when equipped with a dictionary containing more than 2 K word pairs, as shown in Figure 5. Also, VecMap requires bilingual dictionaries or parallel data and has broader language support, while MUSE can be trained with monolingual data alone and has demonstrated a competitive performance in various tasks.

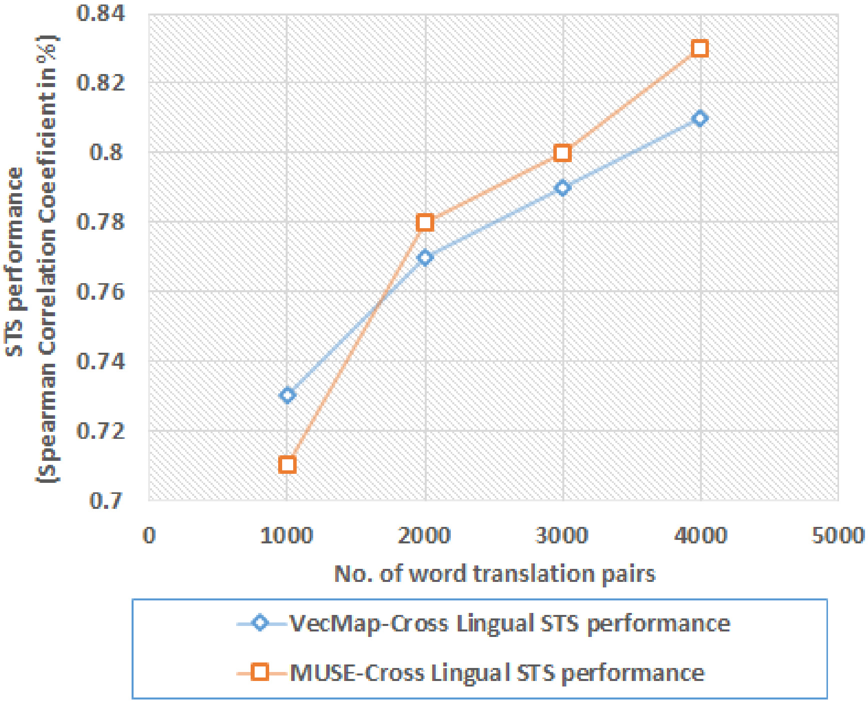


Figure 5. Cross-lingual STS performance.

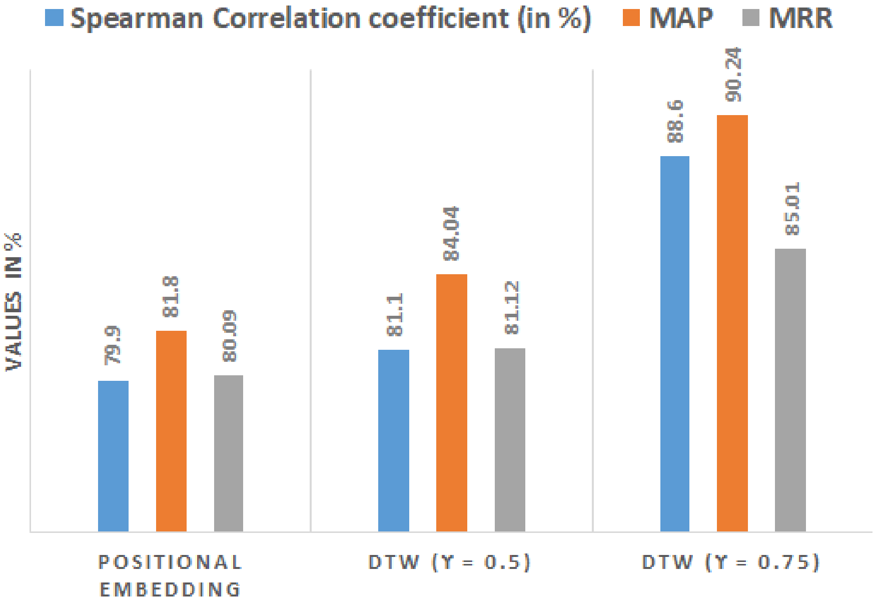


Figure 6. A comparison of cross-lingual STS performance considering word order using positional embedding and DTW.

5. Conclusions

We developed an approach to calculate semantic similarity between two sentences based on embedding space alignment, lexical decomposition, and a CNN. The process of embedding alignment with supervised MUSE performs well for Kannada–English language pairs, even though the Kannada language is morphologically rich and agglutinative. Lexical decomposition and word-order analysis using the DTW mechanism enable the capture of additional semantics in the sentences, which leads to an improved overall performance as measured by the correlation with human annotations. The proposed method also highlights the significance of the bilingual dictionary in achieving a better performance. Developing a lexical database for the Kannada language would facilitate the development of methods to handle semantic-matching-related tasks such as machine translation, information retrieval, and sentiment analysis.

In our future research, we plan to explore the effectiveness of different embedding schemes and different alignment schemes on Kannada–English language pairs for STS. We will also extend the work for other Indian language pairs by using architectures based on modified CNNs. This will allow the model to focus on more relevant parts of the sentences for improved performance. Finally, we are curious to examine the impact of the proposed method on diverse datasets for cross-lingual STS tasks.

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Data Availability Statement: The data that support the findings of this study are openly available in the Samanantar Parallel Corpora Dataset [76], which can be accessed at https://ai4bharat.iitm.ac.in/samanantar (accessed on 11 June 2024).

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