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Article

Leveraging metaphors in qualitative machine translators in the interpretation of emotion

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Abstract: The idea of emotions that is concealed in human language gives rise to metaphor. It is challenging to compute and develop a framework for emotions in people because of its detachment and diversity. Nonetheless, machine translation heavily relies on the modeling and computation of emotions. When emotion metaphors are calculated into machine translation, the language is significantly more colorful and satisfies translating criteria such as truthfulness, creativity and beauty. Emotional metaphor computation often uses artificial intelligence (AI) and the detection of patterns and it needs massive, superior samples in the emotion metaphor collection. To facilitate data-driven emotion metaphor processing through machine translation, the study constructs a bi-lingual database in both Chinese and English that contains extensive emotion metaphors. The fundamental steps involved in generating the emotion metaphor collection are demonstrated, comprising the basis of theory, design concepts, acquiring data, annotating information and index management. This study examines how well the emotion metaphor corpus functions in machine translation by proposing and testing a novel earthworm swarm-tunsed recurrent network (ES-RN) architecture in a Python tool. Additionally, the comparison study is carried out using machine translation datasets that already exist. The findings of this study demonstrated that emotion metaphors might be expressed in machine translation using the emotion metaphor database developed in this research.

Keywords: metaphor; emotions; artificial intelligence (AI); machine translator; emotion metaphor database

1. Introduction

The term machine translation (MT) refers to the process of translating text across languages using software programs. It is a field of language investigation that interprets and generates translations using algorithms and computational linguistics. Neural machine translation (NMT), statistical, and rule-based approaches are some of the ways MT can be implemented. The case of rule-based MT, specialized linguistic rules and dictionaries are in use, whereas in statistical MT, a set of previously translated texts is relied upon to obtain the most probable renderings (Kane, 2020). NMT is a newer and superior methodology that utilizes artificial neural networks to calculate the probability of a word sequence that is normally more fluent and exact than the traditional MT technologies. MT has gained prominence with the entrance of deep learning and big data technologies, but challenges remain in capturing the context, idioms and cultural alignments. It is sailing high in the world of global communication, content localization, real-time communication and information access by easing the language barriers (Zayed et al., 2020).

A metaphor is a type of figurative language that describes something in non-literal terms to help explain an idea or establish a connection, even though the 做

description is not factually accurate. Metaphors assist in that when it comes to the representation of feelings, they present a clearer and more relatable picture in presumably actual terms. For example, describing “anger as a volcano” emphasizes its potential to be quietly simmering before erupting with sudden and devastating force. “Happiness is sunshine”, which takes on the same meaning, evoking coziness and rays coming from a sunny day and spreading the good effect (Liu et al., 2020). These metaphors simultaneously enable to communicate our emotionality more effectively compared to merely speaking about our feelings and also helps to comprehend and process our feelings more profoundly. The role of metaphors is that the complicated, often inappropriate emotions are transformed into visual images that are less confusing and easier to discuss. It is particularly important in the fields of psychotherapy, creative writing and ordinary communication where the ability to correctly resonate feelings is crucial (Dankers et al., 2019).

The issue of translating from Chinese to English is linked to the process of transforming Chinese ideas into English equivalents. The completion of this task is a matter of great difficulty because, in most cases, the grammar, syntax, vocabulary and cultural contexts of the two languages are largely different. Chinese is a group of tonal languages with many varieties and it uses characters instead of alphabets. It has a context and indirect way of saying things as compared to the other languages. In contrast, English is a non-tonal Indo-European language with a fixed alphabet and a tendency toward more explicit communication (Liu, 2022). A good translation implies not just a deep knowledge of both languages but also a feeling of a culture which is reflected in transmitting ideas and emotions. A good literal translation may not do the trick. Therefore, a translator should focus on understanding meaning and intention. It should result in fluent and accurate English equivalents. This ability can be usefully applied in different fields, especially in literature, business and diplomacy, where culturally sensitive and clear communication is essential. Therefore, authentic translation from Chinese to English is an art as well as a technical skill (Bowker, 2020). This investigation proposed a novel earthworm swarm-tuned recurrent network (ES-RN) for how well the emotion metaphor corpus functions in machine translation.

2. Related work

Zeng and Li (2023) utilized Chinese verbs and nouns as test cases for metaphor test analysis. Metaphors have been popular in Chinese language identification, although sentiment analysis remains difficult due to confusing semantics. The results demonstrate improved efficiency despite mutual information and information entropy.

Peng and Jung (2021) proposed a statistical method that utilized contextual emotion mining to determine the emotion distribution of the subject items. The findings show that our method can help readers understand Chinese poetry’s metaphorical and emotional meaning.

Levchenko et al. (2021) proposed a Conceptual Metaphor Theory-based method for automatically recognizing metaphors in linguistically annotated texts. Automated metaphor detection was a difficult task, with solutions mostly designed for English language corpora. Neural networks were employed, although current techniques are unable to identify metaphorical statements. The methodology finds and classifies structural-semantic descriptions of metaphors using word-semantic categories.

Jiang (2023) presented the English literary text into vectors of features and an automated identification approach employing a vector space model. The Bayesian classification method works better than alternative techniques; in Chinese translation and English metaphor identification, the naive bayes Classifiers (NBC) performed better. The research offered a point of reference for translating metaphors found in English literature.

Qian et al. (2023) proposed a Multidimensional Excellence Metrics methodology to assess Machine Translation (MT) technologies on emotion-loaded texts generated by Google Translate. According to the findings, the MT outputs fail to maintain original emotion, including emotion-carrying words and linguistic occurrences serving as common culprits.

Qian et al. (2023) investigated the difficulties encountered by qualified translators and machine translation (MT) in translating emotionally charged material from Chinese microblogs. It demonstrates that emotionally charged words were the most prevalent cause of MT faults.

Hryntus and Dilai (2022) examined emotion metaphors and related metaphorical source regions using a corpus-based analytical method. The ParaSol parallel corpus was used for gathering English and Ukrainian emotional metaphors and fiction abstracts were analyzed to detect emotional metaphors in context. The primary source domains for emotion metaphors were additionally examined.

Su et al. (2019) suggested a Chinese metaphor sentiment evaluation structure that considers context, target and cultural background, further used a “Long Short-Term Memory network (LSTM)” that is attention-based to demonstrate how context and target affect metaphor emotions, addressing the dearth of comprehensive studies on cultural aspects of cross-lingual structures.

Hu and Li (2023) examined the effectiveness of deep learning (DeepL), AI-powered “English-Chinese (E-C)” translating framework and translation of Shakespeare’s events Coriolanus and Venice’s Merchant. The findings demonstrated DeepL’s accuracy and fluency rate at a high percentage, indicating that it’s suitable for translating literature materials between languages.

Terai and Sugyo (2019) presented a metaphor database from a literature corpus to facilitate metaphor generation. Dependency parsing was used to extract and analyze metaphorically rich sentences. An experiment was done to assess the system’s accessibility coupled with its effectiveness, and third-party assessments indicated that the system was effective.

3. Methodology

This research develops a bilingual database of emotion metaphors in Chinese and English to enhance machine translation. It employs an earthworm swarm-tuned recurrent network to test the corpus, demonstrating improved expression of emotional metaphors in translation. The overall flow of the suggested strategy is depicted in **Figure 1**.

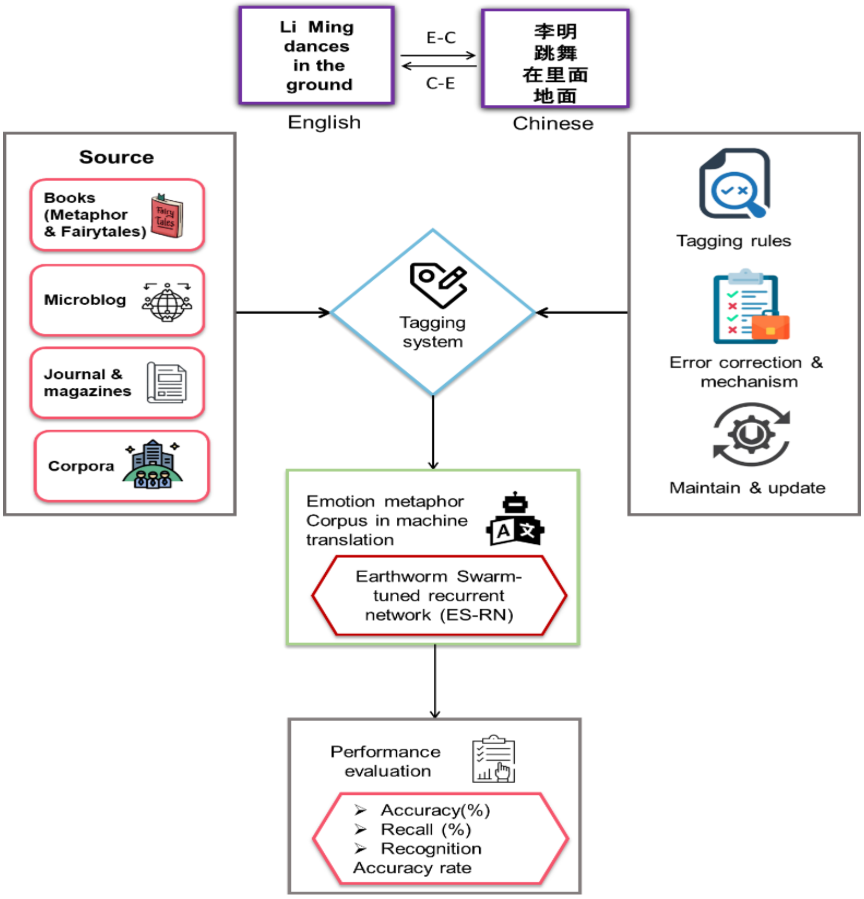

Figure 1. Suggested process flow.

3.1. Fundamental steps

3.1.1. Basis of theory

By the theories and principles of emotional calculation, the emotional boundaries, emotional categories, noumenons, and vehicles must be defined to construct the emotional metaphor corpus. The current research indicates that the boundaries and classification of emotions are confusing. Emotions have been split into 8 or 6 categories and Chinese specialists have further broken those down into 20 subdivisions and 7 main headings. This classifies emotions into seven major heads (sad, hate, angry, happy, surprise, fine, and fear) and twenty-two subdivisions employing the technique for classifying sentiments to provide an improved emotional border theoretical structure and groups. Emotions are categorized into major headings and subcategories in the emotional conceptual structure to make emotion metaphor computing modeling easier.

In addition to emotional boundaries and categories, creating a semantic domain is crucial. The process of mapping known ideas into unknown concepts is known as category location and it is a component of the semantic domain. To calculate emotional metaphors and provide monitorable tags for their identification, the semantic domain must be tagged. This will help create monitorable calculation models.

3.1.2. Design concepts

The research emotion metaphor corpus, which is divided into two sections offline work and online work, aims to support machine translation's emotion metaphor computation. While online work involves data collection during corpus usage by the "machine learning (ML)" method and automatically generated tags by classification of ML, artificial tags are required for offline processing with current corpus data. The following five components comprise the design principles:

i A common set of guidelines and tactics should be used while gathering data on emotion metaphors.

ii There should be consistent ideas and tactics used in the emotions tagging process.

iii For the present corpus's contents, tags and quality to be reflected, quality control and a feedback system are necessary.

iv A searching capability should be included in the design, allowing users to search the entire mapping process using keywords like "ground," "present noumenon," or "metaphor."

v To provide helpful data assistance for the mathematical modeling of machine translation, an interactive mode that is user-friendly is necessary.

3.1.3. Acquiring data

The foundational step in creating a corpus is data collecting. During the data gathering process, the types and contents of the data must guarantee two things: first, diachrony or synchronization; and second, an abundance of emotional information. Basic corpus characteristics include diachrony and synchronization; data exhibiting these traits can reveal the origins, locations and shifting patterns of emotion metaphors. Certain emotive words, like "angry" or "happy," must be understood in light of their historical context and locus to fully grasp the metaphors for the emotions they contain. Some words, like "bursting with happiness" and "afflicted with all ills," require their emotional mapping to be synchronized and understood. Consequently, a corpus of emotion metaphors is only qualified when it contains diachronic or synchronic data that can be used to construct emotion metaphors.

The current research relied on a wide range of sources, including academic journals, magazines, specialized corpora and different book genres. Notably, the corpora are drawn from thematic literature about metaphors and fairy tales, which provide a solid framework for linguistic research. Micro-blogs are also provided to capture current usage and changing linguistic patterns. The emotion metaphor corpus's sources are listed in **Table 1**.

Table 1. Source data for the emotion metaphor corpus.

Sources	Details	Words	Sentences	Pages
Journals and magazines	"Youth Literary Digest", about 33 Journals and magazines	41,827,462	228,628	3636
Corpora	About 28 corpora	1,582,461	138,236	38,849
Books (Metaphors)	Metaphors We Live by", About 10 books	18,456	3792	268
Micro-blog	Whole comments of micro-blog	1,894,351	104,787	39,392
Books (fairy tales)	"Grimms' Fairy Tales", about 4 books	77,872	4996	173

3.1.4. Annotating information

The creation of a corpus is used to help computers learn mathematical modeling, which in turn enables machine translation to produce metaphors for emotions using mathematical models Learning methods with supervision are necessary for mathematical modeling, meaning that every emotion metaphor in a corpus needs to be appropriately annotated or tagged. Regarding The artificial offline tags, the research uses the "Text Encoding Initiative (TEI)" and chooses relevant tags, together with their corpus representations, to tag the data that has been gathered. One of the most effective techniques for resolving tagging ambiguity is TEI; it is quick, easy to use and enhances the precision, consistency and effectiveness of emotion metaphor tagging. The fundamental TEI framework is:

$$\mathrm{MetaphorModel} = (\mathrm{tenor}, \mathrm{vehicle}, \mathrm{ground}, [\mathrm{indicator}], \mathrm{category}, \mathrm{emotion}\ [\mathrm{note}]) \tag{1}$$

Equation (1) identifies the following:

- Tenor is the factor that determines which are assigned,
- vehicle is the source of these attributes,
- ground is the foundation from which we obtain metaphorical statements,
- indicator is the element that piques an emotion,
- categories are a grouping of emotions,
- Boundaries of an emotion are its emotion and a note is a brief commentary about a word. The investigation provides the following examples for the Chinese and English emotion metaphor tags.

Box 1. Examples in Chinese and English.

Chinese example: 李明撐著柔軟如絲的傘在花園裡跳舞，他的舞蹈就像夜晚明亮的月光

(LǐMíngchēngzhe róuruǎnrúsī de sǎn zài huāyuánlǐtiàowǔ, tā de wǔdǎo jiùxiàng yèwǎn míngliàng de yuèguāng: Li Ming dances in the garden with an umbrella as soft as silk, and his dance is like the bright moonlight at night.)

[LǐMíng, B, 11111], [silk, Y, 12313], [soft, D], [PA], [is like D], [moonlight, Y, 12314], [bright, D], [PA]

English example: John dances as gracefully as a leaf in the wind.

[John, B, 11111], [leaf, Y, 12316], [gracefully, D], [PA]

3.1.5. Index management

Index management ensures that the corpus is of high quality. This tagging assignment was completed by seven volunteers, comprising one Chinese instructor, two post-graduates in Chinese, two instructors of English, one English post-graduate and one post-graduate with a computer major. Teachers performed cross-checks while post-graduates worked in teams during the tagging process. The findings were marked as accurate when the cross-check revealed no variations. These seven individuals discussed and documented any discrepancies found during the cross-check process to guarantee accuracy and consistency. 85% of the data had no discrepancies throughout the tagging process, while 15% had differences that were later explored. Ultimately, words were indicated correctly.

Online automatic tagging was implemented in the meantime using an error-correcting method. When the emotions of the metaphorically marked were not consistent with the emotions of the tagged corpus's phrases and the term noumenon, the system rejected all input. This is how the error-correcting mechanism is displayed in Equation (2):

$$\text{flag} = \text{WordConsistency}(M_{\text{emo}}, W_{\text{emo}}) \cap \text{SentConsistency}(M_{\text{emo}}, W_{\text{emo}}) \quad (2)$$

Word Consistency (M_{emo},W_{emo}) and Sent Consistency (M_{emo},W_{emo}) are logged as 1 when tagged outcomes match the emotions of the source words; it is registered as 0 otherwise. Only when "flag" is 1 will the error-correcting process be successful with the labeled findings and be included in the corpus. It has constructed an emotion metaphor corpus that aids in the model construction of English to Chinese machine translation, all under the guidance of five fundamental design principles. The data presented shows the properties of humankind about living and non-living things, specifically in two categories: cars and trains. The evidence for tenors is that 87.61% of the attributes relate to humankind while rather, 2.41% and 9.99% are indicated by living and non-living things, respectively. Vehicles are different from other properties we see, for example, 42.54% of properties are associated with humankind, 23.25% of properties are related to living organisms and 34.21% of properties are non-living things.

4. The corpus of emotional metaphors in machine translation

The investigation employs examples of tagged data and the results of emotion metaphors based on a collection of emotion metaphors already in existence to test and verify the viability of the corpus of emotion metaphors. It also employs machine translation with deep learning techniques to translate the samples, tests and checks the appropriate emotion metaphor outcomes. The typical translation during "natural language processing (NLP)" is predicated on the entire sentence, using another one preprocessing technique Robust scaling. However, in both Chinese and English, contextual links are ubiquitous and words within sentences are intimately related. As a result, the machine translation of each sentence may be viewed as a data series that is chronological. To test the emotion metaphor's tagging outcomes in machine translation for both C-E and E-C translations, because the machine translation process relies on time series data, therefore ES-RN was adopted for how well the emotion metaphor corpus functions in machine translation.

4.1. Robust scaling

An investigation into improving machine translation systems through the integration of robust scaling approaches and metaphorical analysis is presented in Robust Scaling with utilizing metaphors in qualitative machine translators in the Analysis of emotion. Consistent interpretation is ensured by robust scaling, which takes into account linguistic variations in emotional expressions. Metaphors help the system effectively translate emotional material that is subtle and captures deeper contextual meanings. Through this method, the language and cultural divides in emotional communication could be bridged as qualitative machine translators become increasingly adept at recognizing and expressing emotions in translated. Analogous scales are produced from inputs using both standard and robust scalers. What separates them is how raw input data are scaled. Utilizing mean and standard deviation is standard scaling. Rather, interquartile range (IQR) and median are used in robust scaling analyses using Equation (3).

$$\text{Scaled Value} = \frac{\text{Original Value} - \text{Input's Median}}{\text{Input's IQR}} \tag{3}$$

A median of 0 and an IQR of 1 will be assigned to the scaled values. This method improves machine translation's ability to accurately identify and communicate emotions between languages. Incorporating thorough scale and metaphor analysis enhances translators' proficiency in discerning cultural subtleties, resulting in more accurate emotional interpretations and improved cross-cultural communication and empathy with multilingual conditions.

4.2. Earthworm optimization algorithm

The Earthworm optimization Algorithm mimics natural earthworm foraging behaviors for optimal solution search, effectively fine-tuning hyperparameters of machine translation systems and improving how well the emotion metaphor corpus is incorporated, leading to significant improvements in translation accuracy and contextual relevance.

Two different kinds of reproduction occur in earthworms: types 1 and 2.

Reproduction 1: An earthworm can be born to a single parent because they are members of the hermaphrodite group. Equation (4) provides a mathematical formulation of the reproduction process.

$$S_{k1,n} = S_{\max,n} + S_{\min,n} - \eta S_{k,n} \tag{4}$$

The earthworm$k$'s position in Equation (3) is shown by $S_{k,n}$, and its new position is represented by $S_{k1,n}$. $S_{\max,n}$ and $S_{\max,n}$, respectively, stand for the earthworm's lower and upper positions.$S_{k1,n}$ position of the $k1$ earthworm in the n^{th} dimension has been updated. Total earthworms' maximum value in the n^{th} dimension is $S_{\max,n}$. $S_{\min,n}$ the lowest value for each earthworm in the n^{th}dimension. The update is affected by the η control parameter. The present position of the k^{th} earthworm in the n^{th}dimension is denoted by $S_{k,n}$.

ηrepresents the similarity factor, that establishes the separation among the parent and the child. The distance between them is minimal when the similarity factor (η) is small. When $S_{k1}$is close to S_k, the local search takes place. If $\eta = 0$, then there will be a significant distance between them, as shown by Equation (5). The location or fitness of a particular earthworm at iteration n is represented by $S_{k1,n}$. $S_{\max,n}$ represents the optimal fitness value for every earthworm at iteration n . $S_{\min,n}$represents the lowest fitness value at iteration.

$$S_{k1,n} = S_{\max,n} + S_{\min,n} \tag{5}$$

When the similarity factor (η) value is 1, as determined by Equation (6), a global search takes place and this is also considered the optimal-based learning approach. $S_{k1,n}$ represents the value or location of a particular earthworm $k1$ at iteration n .$S_{\max,n}$ represents the highest value among all earthworms at iteration n.The value of $S_{min,n}$ is the lowest value of all earthworms at iteration n. The value or location of another earthworm, k at iteration n is represented by $S_{k,n}$.

$$S_{k1,n} = S_{\max,n} + S_{\min,n} - S_{k,n} \tag{6}$$

Adjustments to the value of ηin reproduction 1 balance the stages of exploration and exploitation. Reproduction 2: $S_{k2}$is calculated using the M offspring for$M = 1, 2,$ and 3 as well as it is theoretically derived in Equation (7). S_{k2} denotes the position or value of a particular earthworm or solution. $\sum_{n=1}^{M}$ represents a over M items or iterations. An iteration-related weight or coefficient, denoted by τ_n. $S_{M,n}$ the value or location of the solution at iteration n this might be a reference to the maximum or particular value in iteration m.

$$S_{k2} = \sum_{n=1}^{M} \tau_n S_{M,n} \tag{7}$$

The weight factor, represented by $\tau_n$in Equation (7), is obtained from Equation (8).

$$\tau_n = \frac{1}{M-1} \frac{\sum_{Y=1,Y\neq n}^{M} H_y}{\sum_{Y=1}^{M} H_y} = \frac{1}{M-1} \cdot \frac{+H_{n+1} + \cdots + H_{n-1} + H_M}{H_1 + H_2 + \cdots + H_{n-1} + H_M + H_{n+1} + \cdots + H_{n-1} + H_M} \tag{8}$$

The fitness of the yth offspring is denoted by H_y in Equation (8). weight or coefficient for the iterationτ_n. M is the sum of the components or iterations. The value of iteration Y is linked to H_y. The total of all $\sum_{Y=1,Y\neq n}^{M} H_y$ values, with the exception of H_n, which indicates the total omitting the value at iteration n, is equal to $\sum_{Y=1}^{M} H_y$. Total of all H_y values across all M repetitions is $\sum_{Y=1}^{M} H_y$. After the two steps of reproduction, the position of l for the following generation is established using Equation (9), where φ represents the proportional factor that affects the value of$S_{k1}S_{k2}$. The following iteration of φ^{s+1}can be obtained in Equation (10).

$$S_k' = \varphi S_{k1} + (1-\varphi) S_{k2} \tag{9}$$

$$\varphi^{s+1} = \lambda \varphi^s \tag{10}$$

In this case λ is equivalent to the constant cooling factor. The performance of the model is impacted by the EOA's usage of the similarity factor to balance local and global search tactics. An algorithm that maintains the responses near to each other is said to concentrate on local search when the similarity factor is minimal. A high similarity factor promotes global search by extending the distance between solutions and preventing local optima, but the strategy rapidly refines current solutions, possibly leading to local optima. Through hyperparameter optimization, adjusting strikes an ideal mix between exploring different concepts and refining existing ones, which is essential for enhancing model performance particularly in the area of emotion metaphor interpretation in machine translation.

4.3. Recurrent neural networks

Recurrent Neural Networks (RNNs) are capable of handling the emotion metaphor corpus in machine translation by recording sequential information in context, improving accuracy in translation for emotionally nuanced and metaphorically complicated texts; however, difficulties remain in uniformity and subtle meaning preservation.

The following equations (11) illustrate thei^{h} node in the network's k^{th} layer:

$$\begin{cases} h_{[f,i]}(R+1) = \sum_{k=1}^{M(f)} U_{[f,i][f,i]}\, R) + \sum_{k=1}^{M(f-1)} U_{[f-1,k]}[f,i]\, y_{[f-1,k]}(R+1) p_{[f,i]}, U_{[r,F]}(f) = L_{[f,i]}\left(y_{[f,i]}(R)\right) \end{cases} \tag{11}$$

where $U_{[f,i]}(R)$ is the weight associated with the link that connects the ith node of the kth layer to the ith node of the r'layer, with $i = 1, \ldots, N(r)$ and $R = 1, \ldots, N$. The condition and output variables of the jth node in the kth layer are represented by $U_{[f,i]}(R)$, respectively, $a_{[k,j]}]$ is the bias to the node. In the r^{h} hidden layer, the jth node's nonlinear discriminating function, $y_{[f,j]}(\cdot)$, serves as a squashing function. The discriminating function for the output layer $(r = R)$ is taken to be linear. The network can presently be broken into three layers: a linear output layer, a nonlinear hidden layer, and an input layer that serves as a buffer. That most types of nonlinearities found in reality can be adequately approximated by a single hidden layer network of these varieties following the Equations (12) and (13).

$$y_{[f,j]}(\cdot), = \hat{x}_i(\cdot), for\ j = 1, \ldots, M \tag{12}$$

The vector representation of an o-step-ahead predictor is as followed by Equation (13).

$$\begin{cases} y(l + o(l) = E(\mathcal{X}_{2\to2}y(l + o - 1/l) \\ \quad +\mathcal{X}_{1\to2}\hat{V}\left(l + o - {}^{1}/_{l}\right) + a_{[2]}), \\ \hat{z}(l + {}^{o}/_{l}) \ = \mathcal{X}_{2\to3}y(l + {}^{o}/_{l})a_{[3]} \end{cases} \tag{13}$$

where $M(1)$ is the number of hidden nodes, and $F(\cdot)$ is an $M(2)$ dimensional vector holding the discriminating functions of the hidden layer. Given observations up to time k, the conditioned value of the hidden layer state vector is also an $M(3)$ dimensional vector and is represented by using the Equations (14)–(18).

$$z\left(k + \frac{k}{p}\right) = [z_{[2,1]}(k + \frac{p}{k}, \ldots., z_{[2,N(2)]}(q + p/k)]^T \tag{14}$$

$$b_{[i]} = [b_{[i,2]}, \ldots., b_{[i,N(i)]}]^T \tag{15}$$

assuming $i\ = 2$ and 3.

$$Y_{1\to2} = \left[Y_{[1,i][2,i]}; I = 1, \cdots, N(1); j = 1, \cdots, N(2)\right] \tag{16}$$

And:

$$Y_{2\to3} = [Y_{[2,i][3,j]}; I = 1, \cdots, N(2); j = 1, \cdots, N(3)] \tag{17}$$

The feed forward weights:

$$Y_{2\to2} = [y_{[2,j][2,i]}; i = 1, \ldots.., N(2); j = 1, \ldots., N(2)] \tag{18}$$

where $Y_{1\to3}, Y_{2\to2}, Y_{2\to3}, a_{[2]}$ and $a_{[3]}$ are included, which characterize the RNN.

Machine translation performance of emotionally nuanced and metaphorically complex texts is greatly improved when RNN are integrated with sophisticated structures such as RNN. Through the use of RNN gate mechanisms to solve long-term dependence issues and fewer parameters to improve training efficiency, these models effectively identify complex patterns and keep complex meanings. This progresses the field of language processing towards more complex and nuanced application by improving translation accuracy and contextual information interpretation.

4.4. Earthworm optimization and recurrent neural network (ES-RN)

The mixed model of Earthworm Optimization and Recurrent Neural Network (ES-RN) shows a new way for an improvement of the abilities of qualitative machine translators, especially in the sphere of decoding emotions within metaphors. By bringing together the flexibility and the global search characteristics of Earthworm swarm (ES) with the capability of RN to process temporal sequences, this hybrid model successfully addresses the complicated task of metaphor interpretation. EO's algorithm adjusts the network parameters for quick learning and high adaptability, while RNN focuses on text comprehension and sequential data understanding. The cooperation allows for more intricate and psychologically sensitive metaphor translation exceeding the world of language understanding by machines. Enhancing pattern identification and adaptability in dynamic contexts, the ES-RN combines RN with ES. It enables sophisticated comprehension of the emotional context of words when combined with metaphors in qualitative machine translation. This combination of techniques improves the quality of machine-generated translations in emotional situations by applying metaphorical language models to properly interpret and transmit emotions and using swarm optimization to fine-tune neural networks for improved emotional comprehension.

5. Result and discussion

We implemented our approach in Python (v 3.12) on Windows 11 OS. The system is driven by an Intel Core i9 processor and features a high-performance IRIS graphics card, delivering strong capacity for executing demanding machine learning applications. The effectiveness of the suggested method (ES-RN) was analyzed by applying a set of parameters including accuracy and run time compared with existing methods traditional methods and"machine learning(ML)" (Fu, 2022). An analysis graph of the traditional and proposed methods is illustrated in **Figure 2** and **Table 2**. It shows that our proposed method is effective than the traditional method.

Table 2. Performance comparison in traditional and ES-RN.

Metric	Traditional Method	ES-RN [Proposed]
Accuracy (%)	79.8	90.6
Recall (%)	89.7	89.7
Recognition Accuracy Rate	88.9	89.9

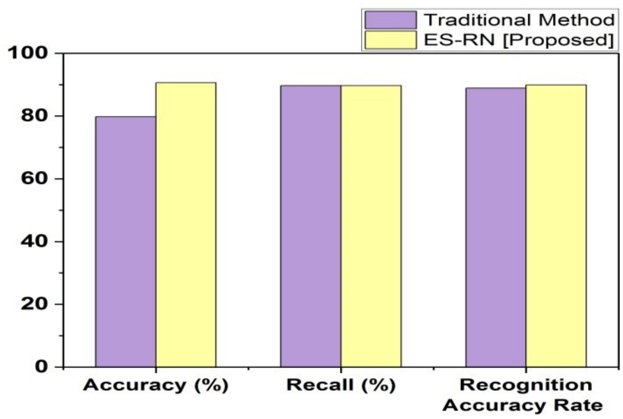

Figure 2. Traditional vs. proposed method.

Accuracy: The accuracy of the translation system is determined by comparing the number of correct translations to the total number of translations analyzed. This ratio shows how accurately the system interprets emotional metaphors. **Figure 3** shows the comparison result for accuracy. The suggested method shows that a greater accuracy (98.2%) rate it can lead to better performance than existing (97.4%) for the emotion metaphor corpus in machine translation.

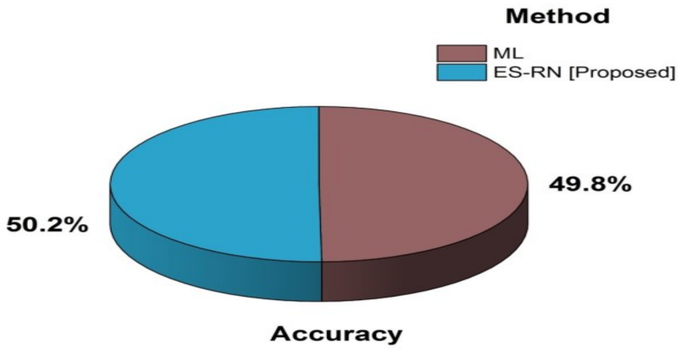

Figure 3. Result of accuracy.

Recall: Recall measures a machine's ability to accurately identify and understand each emotional metaphor in the source and destination languages, ensuring high recall and preventing erroneous or poorly translated translations. **Figure 4** shows the comparison result of the recall. The proposed method indicates that a higher recall (87.4%) rate that leads to improved performance than the existing approach (65.5 %) for the emotion metaphor corpus in machine translation.

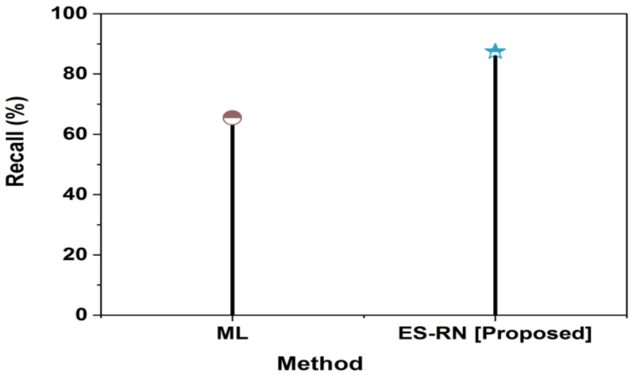

Figure 4. Result of recall.

Recognition accuracy rate: The metric assesses the accuracy of recognizing and translating emotional metaphors in a text, distinguishing between general and metaphor-specific accuracy to provide a more complete assessment. **Figure 5** shows the comparison result of the recognition accuracy rate. The suggested method shows that a greater recognition accuracy rate (90%) can lead to better performance than the existing method (83%) for the emotion metaphor corpus in machine translation. **Table 3** shows the numerical comparison in proposed method.

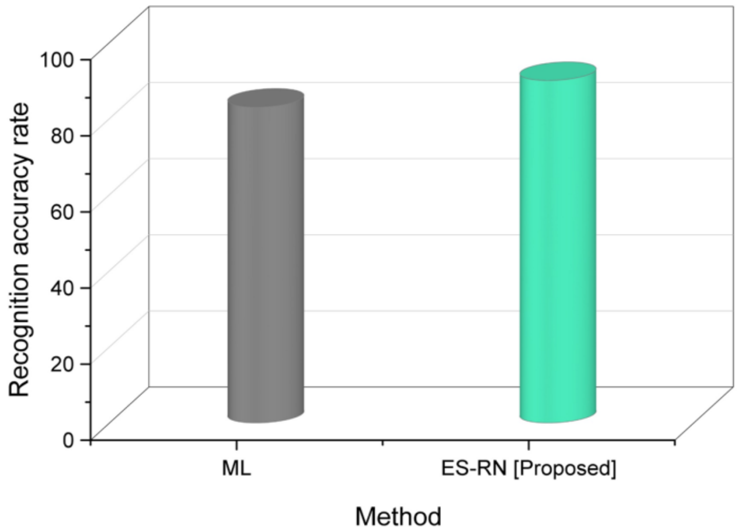

Figure 5. Result of recognition accuracy rate.

Table 3. Numerical comparison in proposed method.

Method	Accuracy	Recall (%)	Recognition accuracy rate
ML	97.4	65.5	83
ES-RN [Proposed]	98.2	87.4	90

6. Discussion

Though using ML into qualitative machine translators to analyze emotions can improve comprehension, there is significant disadvantages. The inability of existing ML algorithms to comprehend context and complexity can lead to the misreading of complex emotional expressions. Furthermore, depending too much on metaphorical language might result in an oversimplification or distorting of the intended emotional significance. The purpose of the data collection using ES-RN to maximize swarm intelligence for the detection and classification of emotional metaphors. This method improves model performance and pattern recognition, guaranteeing better and more complete samples for precise and effective emotion metaphor computation. To improve RNN training, a novel technique called ES-RN uses an optimization strategy modeled by the behaviors of earthworm swarms. ES-RN seeks to enhance model accuracy and efficiency in tasks including emotion metaphor computation and machine translation by fine-tuning RNN parameters using this swarm-based approach. The emotional analysis of existing ML algorithms is hindered by metaphorical language and context, which can lead to misunderstandings. To more effectively grasp and preserve complex emotional expressions, our suggested strategy, ES-RN, improves context sensitivity and flexibility.

7. Conclusion

Research emphasizes the fact that the mention of emotions in machine translation brings computational difficulties. It is however important that emotions in language be captured for the sake of enhancing translation quality. With the help of the Chinese and English bilingual emotion metaphor database, AI-powered processing can be enhanced in this field. The proposed earthworm swarm-tuned recurrent network (ES-RN) architecture has made remarkable advancements and surmounted existing models using standard datasets. Such an approach not only helps to develop advanced tools for processing emotional dimensions in translation but also meets key criteria for translation such as truthfulness, creativity and beauty, adding more appeal to linguistic products. The quality and appropriateness of the emotional metaphor corpus can be one limitation. When the data is not well-prepared or is not representative of different languages, styles, or emotional expressions in the corpus, it will lead to translation biases or inaccuracies. The main objective in the future should be to make further improvements in the curation and variety of the corpus of emotion metaphors, which include the addition of other languages, types and styles of emotional nuances. As a result, computer translation systems will be less biassed towards other cultures and more accurate overall.

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