Metaphorical Meaning Integration in Poetry Based on Online Discourse Data: Analysis from a Cognitive Linguistics Perspective

Ying LIU, Jiting XUE*
Mudanjiang Medical University, Mudanjiang 157000, Heilongjiang, China

***Abstract*—As an emerging literary form, online poetry has garnered significant attention due to its rapid dissemination, diverse styles, and complex metaphorical expressions. However, the process of metaphorical meaning integration in poetry is difficult to quantify, necessitating support from Artificial Intelligence technologies. This study integrates cognitive linguistics theory with AI algorithms to propose a three-dimensional fusion analysis framework—"cognitive theory + specific AI algorithms + online discourse data"—for dissecting metaphorical meaning integration in online poetry. By constructing a comprehensive methodology encompassing metaphor identification, semantic mapping, and integration analysis, this study offers a novel quantitative pathway for metaphor research in poetry. Experimental validation demonstrates that the integrated approach—leveraging Support Vector Machines (SVM), Convolutional Neural Networks (CNN), BERT pre-trained models, and the DeepSeek-R1 large model—achieves outstanding performance in metaphor recognition accuracy, semantic association quantification, and fusion effectiveness evaluation, fully embodying both theoretical and practical value.**

Keywords—Online discourse data; poetic metaphor; cognitive linguistics; Artificial Intelligence; semantic fusion

I. Introduction

As a significant form of literary creation in the internet era, online poetry has gradually become an integral part of popular culture due to its rapid dissemination, diverse styles, and strong interactivity [1]. Metaphorical expressions in poetry not only carry rich cultural and emotional connotations but also reflect unique human thought patterns and cognitive mechanisms [2]. However, the process of metaphorical meaning integration is complex and difficult to quantify, urgently requiring systematic analysis through Artificial Intelligence technologies [3]. Recent breakthroughs in AI for natural language processing have opened new avenues for metaphor research. Algorithms like Support Vector Machines (SVM) [4] and Convolutional Neural Networks (CNN) [5] excel in text classification and feature extraction, while pre-trained models such as BERT [6] and DeepSeek-R1 [7] demonstrate immense potential in semantic analysis and reasoning. Based on this, the study proposes a three-dimensional integrated analytical framework combining "cognitive theory + specific AI algorithms + online discourse data". This framework aims to build a bridge between cognitive linguistics and AI technology, providing quantitative methods for poetic metaphor research.

From a cognitive linguistics perspective, poetic metaphor research primarily revolves around conceptual metaphor theory and conceptual integration theory [8]. Metaphor is a cognitive mechanism that achieves semantic transfer by mapping one conceptual domain onto another. In [9], the authors demonstrate this by mapping time onto money, endowing it with economic attributes. In [10], the authors elucidate the cognitive mechanism of metaphor, emphasizing that during cross-domain mapping, the integration of features from different conceptual domains forms a new semantic space. These theories provide a foundation for semantic analysis of poetic metaphors, though they remain insufficient for quantifying metaphor fusion effects.

In the field of AI algorithms, text metaphor recognition and semantic parsing technologies continue to advance. In [11], Support Vector Machines (SVM) demonstrated strong performance in metaphor classification tasks, effectively distinguishing metaphorical from non-metaphorical sentences. In [12], CNNs further enhance metaphor recognition accuracy through local contextual feature extraction. In [13], the BERT pre-trained language model offers novel insights for metaphorical meaning mapping via contextual semantic encoding. However, existing research predominantly focuses on metaphor identification, with limited in-depth analysis of metaphorical meaning fusion and a lack of theoretical support for cognitive mechanisms.

Furthermore, specialized research on metaphors in online poetry remains scarce. The dissemination characteristics and metaphorical expressions of online poetry possess unique traits. Its multi-thematic and diverse nature provides rich corpora for metaphor studies, yet existing research has failed to fully leverage these data [14]. Simultaneously, the training challenge for low-resource poetry corpora demands urgent solutions, with transfer learning and self-supervised learning offering potential approaches [15].

However, current research exhibits the following shortcomings: First, the integration of cognitive linguistics theories with AI algorithms remains superficial, with most studies confined to theoretical exposition and algorithmic application without in-depth exploration of their fusion mechanisms [16]. Second, research on metaphors in online poetry is scarce, failing to fully leverage the distinct characteristics of online discourse data [17]. Third, quantitative methods for analyzing metaphorical meaning fusion remain immature, lacking systematic evaluation metrics for fusion effectiveness [18].

*Corresponding author.

Addressing these gaps, this study constructs a three-dimensional integration framework combining specific algorithms with online discourse data to investigate metaphorical meaning integration in online poetry. Its main contributions are threefold: 1) Establishing a “cognitive theory + specific AI algorithms + online discourse data” framework that systematically outlines the integration pathway between cognitive linguistics and AI technology; 2) through constructing a web poetry corpus and performing data preprocessing, designed metaphor recognition, semantic mapping, and fusion analysis algorithms based on SVM, CNN, BERT, and DeepSeek-R1. This achieves end-to-end analysis of metaphorical meaning fusion, providing concrete algorithms and experimental validation for quantitative research on poetic metaphors; and 3) based on experimental results, quantitative evaluation metrics for metaphor fusion effectiveness were proposed, including metaphor recognition accuracy, semantic relevance, and fusion degree. These metrics validated the algorithms' efficacy and reliability, offering practical guidance for applied research in poetic metaphor studies.

II. Theoretical Foundations and Technical Support

A. *Core Theories of Cognitive Linguistics*

Cognitive linguistics provides three core theories for understanding metaphor: conceptual metaphor theory, conceptual integration theory, and image schema theory [19].

Conceptual metaphor theory, proposed by Lakoff and Johnson, posits that metaphor is a cognitive phenomenon involving the mapping of one conceptual domain (source domain) onto another conceptual domain (target domain) [20]. Fig. 1 illustrates the cross-domain mapping process in conceptual metaphor theory, visually representing the relationship between source and target domains and how mapping endows the target domain with new semantic features.

Fig. 1. Conceptual metaphor mapping diagram.

Conceptual integration theory further elucidates the cognitive mechanisms of metaphor. Proposed by Fauconnier and Turner, this theory emphasizes the integration of features from different conceptual domains within metaphorical expressions [21]. The cognitive process of metaphor involves four Mental Spaces: Input Space 1 (source domain), Input Space 2 (target domain), the Category Space (shared features), and the Fusion Space (integrated features). Through cross-domain mapping and feature integration, metaphorical expressions form new semantic spaces that aid in constructing and understanding complex conceptual relationships.

The mental schemata theory, grounded in human cognitive patterns, posits that metaphorical expressions rely on cognitive schemata of typical images, including “container schemata”, “path schemata”, and “spatial schemata” [22]. These schemata originate from human perception and experience, forming the foundation for understanding abstract concepts.

B. *Core Algorithmic Principles of Artificial Intelligence*

1) Metaphor recognition algorithms: Support Vector Machines (SVM) is a supervised learning algorithm based on statistical learning theory. It classifies data into distinct categories by identifying the optimal separating hyperplane [23]. For metaphor recognition tasks, SVM utilizes inputs such as word vectors and part-of-speech features to train classifiers that distinguish metaphorical sentences from non-metaphorical ones. The strength of SVM lies in its classification performance in high-dimensional spaces, enabling effective handling of complex textual features.

Convolutional Neural Networks (CNN) extract local contextual features through convolutional layers, reduce feature dimensions via pooling layers, and perform classification using fully connected layers [24]. CNN excels at capturing local textual features, particularly adept at identifying key words and phrases within metaphorical expressions.

Fig. 2 illustrates the metaphor recognition workflow of the SVM-CNN fusion algorithm, encompassing text feature extraction, feature vector generation, and classification prediction. This demonstrates how the two algorithms synergize to enhance metaphor recognition accuracy. Table I compares the performance of SVM and CNN in metaphor recognition tasks, including accuracy, recall, training efficiency, and applicable scenarios, providing a reference for selecting the appropriate algorithm.

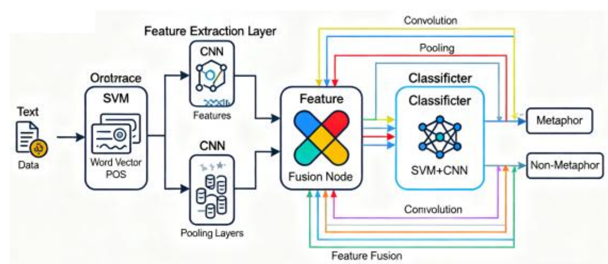

Fig. 2. Metaphor recognition using SVM and CNN fusion.

TABLE I. Comparison of SVM and CNN in Metaphor Recognition

Performance indicators	*SVM*	*CNN*
Accuracy	High, especially in high-dimensional feature spaces	High, especially in capturing local contextual features
Recall	Stable suitable for handling imbalanced datasets	Stable sensitive to local features suitable for complex contexts
Training efficiency	Low, especially on large-scale datasets	High suitable for large-scale data training
Applicable scenarios	High-dimensional feature spaces such as word vector representation	Local context feature extraction such as keyword and phrase recognition

2) Semantic analysis algorithm: BERT is a pre-trained language model based on the Transformer architecture [25]. It captures contextual semantic information in text through pre-training with the Masked Language Model (MLM) and Next Sentence Prediction (NSP) tasks. In metaphorical meaning mapping tasks, BERT encodes metaphorical sentences to generate semantic vectors, quantitatively analyzing the semantic association strength between the referent domain and the metaphorical domain. Fig. 3 illustrates how the BERT model performs contextual semantic encoding of text to generate semantic vectors.

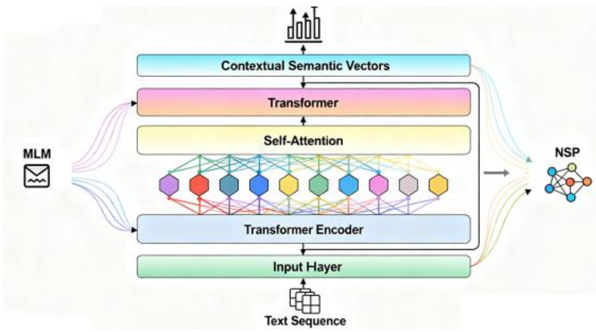

Fig. 3. BERT contextual semantic encoding logic.

DeepSeek-R1 is a large language model with robust deep semantic reasoning capabilities. It can analyze the cognitive logic behind metaphors, reconstructing the transformation and restructuring processes of imagery schemas [26]. Through its multi-layer neural network architecture, DeepSeek-R1 captures deep semantic features in text, offering a novel approach to cognitive analysis of metaphors. Fig. 4 illustrates the working principle of the DeepSeek-R1 large language model.

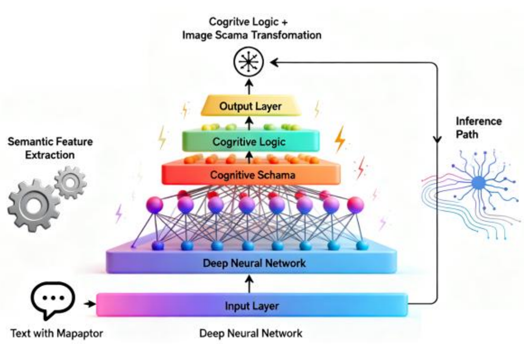

Fig. 4. DeepSeek-R1 schematic diagram.

3) Data processing algorithms: The application of transfer learning and self-supervised learning in low-resource poetry corpora holds significant importance. Transfer learning addresses the training challenges of low-resource poetry corpora by transferring knowledge from the source domain to the target domain [27]. Self-supervised learning leverages unlabeled data to learn textual features through tasks such as predicting masked words, thereby enhancing the model's generalization capability [28]. Fig. 5 illustrates the workflow of applying transfer learning and self-supervised learning to low-resource poetry corpora, encompassing pre-trained model transfer, feature extraction, and self-supervised task design. This demonstrates how these algorithms enhance the utilization efficiency of low-resource corpora.

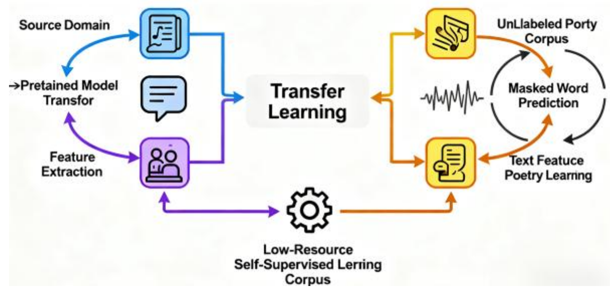

Fig. 5. Transfer learning and self-supervised learning in low-resource poetry corpora.

C. Application of Online Discourse Data in Integrating Metaphorical Meanings in Poetry

Online poetry corpora exhibit diversity, interactivity, and dynamism, providing rich practical scenarios for metaphorical meaning integration research.

Online poetry encompasses diverse themes and styles, featuring abundant metaphorical expressions. Readers participate in poetry dissemination through comments, shares, and other forms, fostering multidimensional metaphorical interpretations. This study constructed an online poetry corpus by collecting texts from poetry forums, social media, and other platforms, selecting representative metaphorical poems. Through corpus preprocessing and annotation, it provided data support for algorithm training.

During metaphorical meaning integration, the interactive nature of online discourse data provides multi-faceted information for semantic analysis. Reader comments and interpretations enrich the semantic layers of metaphors, enhancing the comprehensiveness of integration analysis. Simultaneously, the dynamic nature of the data requires algorithms to possess real-time updating and adaptive capabilities to address newly emerging metaphorical expressions in poetry. The formula for calculating metaphor integration is as follows:

$$FusionDe = \frac{\sum_{i=1}^{n} SemanticAs(i)}{n} \tag{1}$$

Here, $FusionDe$ represents metaphor fusion degree, $SemanticAs(i)$ denotes the association strength between the referent domain and the metaphor domain on the i-th semantic dimension, and n is the total number of semantic dimensions. This formula quantifies the fusion effect of metaphorical meaning in the synthetic space.

III. Research Design and Data Preprocessing

Before conducting research on the fusion of metaphorical meaning in online poetry, a systematic research design and data preprocessing are required. This section encompasses the construction of an online discourse poetry corpus, the establishment of data preprocessing procedures, and the selection of appropriate algorithms.

A. Construction of the Online Discourse Poetry Corpus

Building a high-quality online discourse poetry corpus forms the foundation of this research. Corpus construction requires identifying data sources and establishing rigorous screening criteria to ensure diversity and representativeness.

1) Corpus sources: Online poetry data primarily originates from poetry platforms, forum comments, and social media shares [29]. Fig. 6 illustrates the main collection sources and distribution of poetry data, visually representing each platform's contribution ratio. The figure reveals that social media shares constitute a significant proportion, indicating the substantial influence of poetry dissemination on social media.

Fig. 6. Distribution map of poetry corpus collection sources.

Online poetry platforms include China Poetry Network and Poetry Journal Forum, which aggregate a vast collection of original poetry works, typically possessing high literary value and artistic merit. Forum discussions encompass platforms like Douban Poetry Group and Zhihu Poetry Topics, where poetry sharing and commentary provide rich interactive data. Social media sharing encompasses platforms like Weibo and WeChat Official Accounts, where poetry reposts and comments reflect dissemination popularity. Table II summarizes the volume of poetry corpora from various sources alongside dissemination metrics, offering a comprehensive overview of the corpus's overall characteristics. Poetry shared via social media demonstrates particularly prominent dissemination popularity, closely tied to its rapid propagation nature.

TABLE II. POETRY CORPUS STATISTICS

Platform type	*Number of poems*	*Average reads*	*Average likes*	*Average comments*
Online poetry platforms	1200	1500	120	30
Forum comments	800	800	60	20
Social media sharing	1000	2000	150	40

2) Corpus screening criteria: To ensure the quality and representativeness of the corpus, the following screening criteria were established:

Thematic diversity. Covering multiple common poetic themes such as love, nature, life, and society to ensure richness in metaphorical expression.

Metaphor density. Poems with high metaphor density better reflect the complexity and diversity of metaphorical expression, providing more meaningful data for subsequent algorithmic analysis. Metaphor density is calculated as follows:

$$MetaphorDensity = \frac{n_{Metaphors}}{n_{Sentences}} \tag{2}$$

Among these, $MetaphorDensity$ denotes metaphor density, $n_{Metaphors}$ represents the number of metaphors per poem, and $n_{Sentences}$ indicates the total number of lines per poem. Fig. 7 illustrates the distribution of metaphor density within the selected poetic corpus, reflecting its diversity and analytical value. The figure reveals that poems with metaphor densities exceeding 30% constitute a significant proportion, indicating that the selected corpus exhibits a high richness of metaphorical expression.

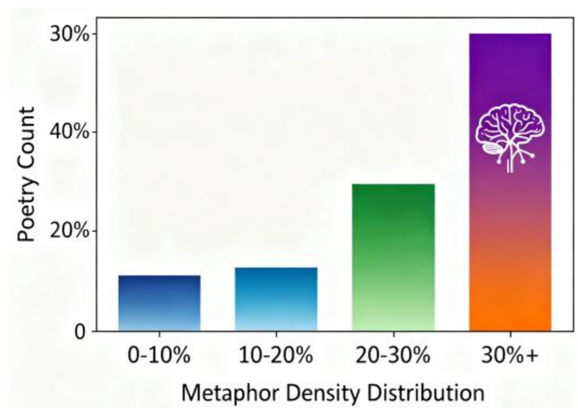

Fig. 7. Metaphor density distribution map.

Virality. Popular poems are selected based on metrics such as reading volume, likes, and comments to ensure the corpus's influence and representativeness.

B. Data Preprocessing Workflow

Data preprocessing is a critical step to ensure corpus quality, encompassing text cleaning, feature annotation, and data format conversion.

1) Text cleaning: The purpose of text cleaning is to remove irrelevant symbols, duplicate content, and non-poetic text to enhance corpus purity [30]. Specific operations include: 1) Removing irrelevant symbols. Using regular expressions to eliminate punctuation marks, emoticons, and other extraneous characters from poetic texts; 2) Removing duplicate content. using text deduplication algorithms to eliminate duplicate poetic paragraphs or entire poems; 3) Removing non-poetic text. Filtering out pure poetic text while discarding non-poetic content like author biographies and copyright notices. Fig. 8 illustrates the specific text cleaning workflow, encompassing steps to eliminate irrelevant symbols, duplicate content, and non-poetic text. These procedures effectively enhance corpus purity and quality.

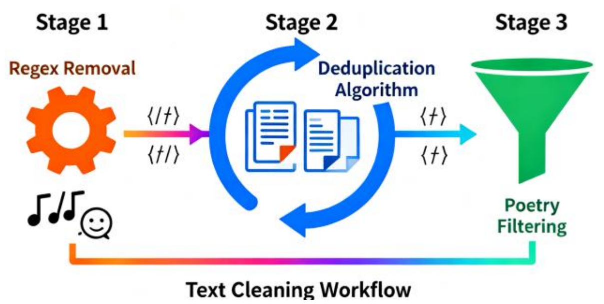

Fig. 8. Text cleaning flowchart.

2) Feature annotation: The purpose of feature annotation is to identify and annotate metaphor-related vocabulary, laying the foundation for subsequent metaphor recognition and semantic analysis. Specific operations include:

a) Word segmentation and part-of-speech tagging. Using the jieba tokenization tool to segment the poetry text and annotating the part-of-speech for each word using the part-of-speech tagging module; b) Metaphor-related lexical annotation. Based on the part-of-speech annotation results, identifying and annotating metaphor-related lexical items (nouns, verbs, adjectives); c) Manual correction. Incorporating manual correction to enhance the accuracy of feature annotation.

3) Data format conversion: The purpose of data format conversion is to transform textual data into a vector form processable by AI algorithms. Specific operations include:

Word Embedding. Employing the Word2Vec algorithm to convert words into fixed-length vector representations. By training on large text datasets, Word2Vec captures semantic and syntactic features of words, mapping them into a continuous vector space. Fig. 9 illustrates the Word2Vec embedding process, including generating word vectors and combining sentence vectors. Through extensive text training, Word2Vec generates high-quality word vectors that provide robust support for subsequent model training.

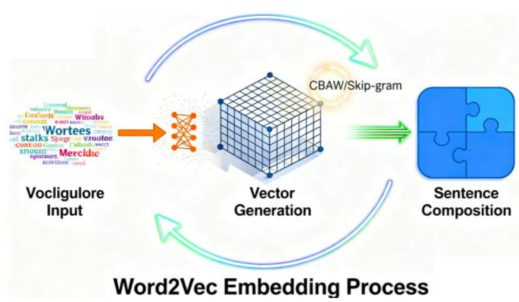

Fig. 9. Word2Vec lexical embedding process diagram.

Sentence Vectorization. Combine lexical vectors into sentence vectors to form the vector representation of a poem. By averaging or weighting the lexical vectors, we obtain the vector representation of the sentence, which serves as input data for model training. The sentence vector calculation formula is as follows:

$$SentenceVector = \frac{1}{n}\sum_{i=1}^{n} WordVector(i) \quad (3)$$

Here, $WordVector(i)$ represents the vector representation of the i-th word in the sentence, and n denotes the number of words in the sentence. This formula calculates the sentence vector by combining word vectors into a vector representation of the sentence. This approach converts poetic text into a numerical format that the model can process.

C. Algorithm Selection

Selecting appropriate algorithm combinations is crucial for metaphor recognition and semantic analysis in this research. This study specifies the following combinations:

a) SVM+CNN for metaphor recognition, leveraging SVM's classification capability and CNN's local context feature extraction. SVM excels at classification in high-dimensional spaces, while CNN effectively extracts local textual features. Their integration enhances metaphor recognition accuracy.

b) BERT + DeepSeek-R1 for semantic analysis, leveraging BERT's contextual semantic encoding and DeepSeek-R1's deep semantic reasoning capabilities. BERT captures contextual semantic information in text, while DeepSeek-R1 excels in deep semantic reasoning. Their integration enables a comprehensive analysis of metaphorical semantic features.

c) Transfer learning is employed for low-resource corpus optimization, enhancing model performance on sparse data by transferring knowledge from pre-trained models. This approach effectively addresses training challenges in low-resource settings and improves model generalization.

Fig. 10 illustrates the overall framework of algorithmic integration, encompassing combinations for metaphor recognition, semantic analysis, and low-resource corpus optimization. By integrating multiple algorithms, the strengths of each are leveraged to elevate the model's overall performance.

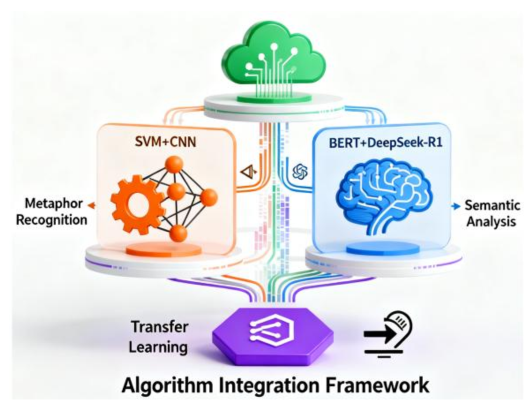

Fig. 10. Algorithm integration framework diagram.

D. Data Augmentation and Expansion

To further enhance the model's generalization capability and robustness, this study introduces data augmentation techniques. Through data augmentation, more training examples can be generated to enrich the diversity of the corpus.

Data augmentation operations include synonym substitution, sentence reordering, and sentiment reversal. 1) Synonym Substitution: Randomly replace selected words in poetic texts with synonyms while preserving overall sentence meaning. 2) Sentence Rearrangement. Generate new sentence combinations by adjusting sentence structure and order; 3) Sentiment Reversal. Invert the emotional orientation of sentences while preserving their core meaning. Fig. 11 illustrates the principles behind synonym substitution, sentence rearrangement, and sentiment reversal. These methods effectively enrich corpus diversity and enhance model generalization capabilities.

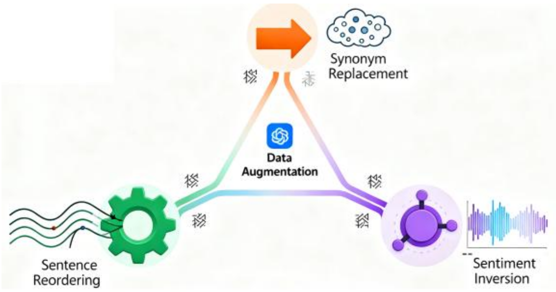

Fig. 11. Principles of data augmentation.

IV. AI Algorithm Implementation Path

Following the construction of the network discourse poetry corpus and data preprocessing, this section details the AI algorithm implementation path for integrating metaphorical meanings in poetry. Three core modules are designed: metaphor recognition, semantic mapping, and fusion analysis. These modules collaborate to achieve end-to-end processing from metaphor identification to semantic integration.

A. Metaphor Recognition Module

Metaphor recognition serves as the initial step in integrating poetic metaphorical meanings, with its accuracy directly impacting subsequent semantic analysis and fusion outcomes. This study employs a combined SVM and CNN algorithm for metaphor recognition, leveraging SVM's classification capabilities in high-dimensional feature spaces and CNN's strengths in extracting contextual features.

Feature input is a critical step in metaphor recognition, directly affecting model performance. This study constructs a comprehensive feature vector based on Word2Vec-generated word vectors, supplemented with part-of-speech features and contextual window features: 1) Word2Vec Word Vectors. A pre-trained Word2Vec model converts words into fixed-length vector representations, capturing semantic and syntactic features. 2) Part-of-speech features. Based on part-of-speech tagging results, the part-of-speech information of metaphor-related vocabulary, such as nouns, verbs, and adjectives, is encoded into feature vectors; 3) Context window features. Centering on the target vocabulary, fixed-size windows are set to the left and right to extract co-occurrence features of words within the window, capturing local contextual information.

The fusion algorithm process includes the following steps: First, CNN extracts local contextual features from the text, with CNN automatically learning local feature representations through convolutional and pooling layers. Next, the feature vectors extracted by CNN are input into an SVM classifier for classification, achieving binary classification of "metaphorical sentence/non-metaphorical sentence", and further subdividing metaphor types to annotate the subject-metaphor relationship. Fig. 12 illustrates the complete workflow of the SVM-CNN fusion algorithm, encompassing feature input, CNN feature extraction, feature vector generation, and SVM classification prediction, demonstrating the synergistic interaction between the two algorithms. Table III summarizes the dimensionality of different feature types within the metaphor recognition module, providing a detailed reference for feature engineering.

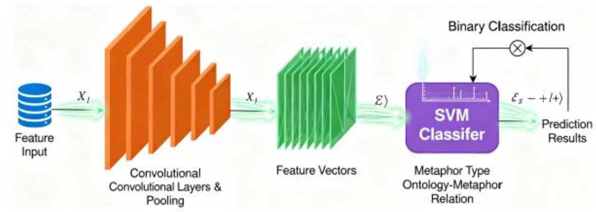

Fig. 12. SVM-CNN fusion algorithm.

TABLE III. Statistics of Metaphor Recognition Feature Input Dimensions

Feature type	***Dimension size***	***Description***
Word2Vec word vector	300	Word vector dimension
Part-of-speech features	10	One-hot vector dimension for part-of-speech tagging
Contextual window features	200	Co-occurrence feature vector dimensions extracted from the window

B. Semantic Mapping Module

After completing metaphor recognition, the next step involves performing semantic analysis on the identified metaphorical sentences. This entails constructing semantic vector spaces for the referent domain and the metaphor domain, followed by quantifying the semantic association strength between them. This study employs the BERT pre-trained model to build the semantic vector space.

BERT is a pre-trained language model based on the Transformer architecture. Through pre-training on large-scale text data using masked language modeling and next-sentence prediction tasks, BERT learns contextual semantic information from text, providing powerful semantic representations for various natural language processing tasks.

For identified metaphorical sentences, the BERT model first encodes them to generate contextual semantic vectors for each lexeme. Subsequently, semantic vector spaces for the referent domain and metaphor domain are constructed based on these lexical vectors. Specifically, the lexical vectors belonging to the referent domain within the metaphorical sentence undergo average pooling to obtain the referent domain's semantic vector. Similarly, average pooling is applied to the lexical vectors of the metaphor domain to obtain its semantic vector. Fig. 13 illustrates the process of semantic encoding for metaphor sentences using BERT and how the semantic vector spaces for the ontology domain and metaphor domain are constructed, providing data support for subsequent concept mapping.

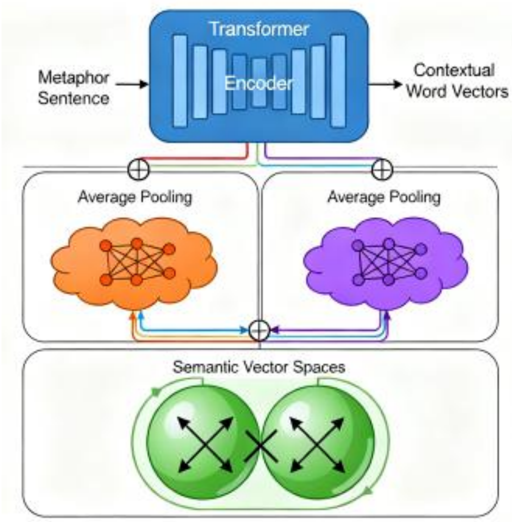

Fig. 13. BERT semantic encoding and semantic vector space construction.

To quantify the semantic association strength between the referent domain and the metaphor domain, the cosine similarity between their semantic vectors is computed. Cosine similarity measures the directional similarity between two vectors; values closer to 1 indicate stronger semantic association.

$$SemanticSimilarity = \frac{OntologyVector \cdot MetaVector}{\|OntologyVector\| \times \|MetaVector\|} \quad (4)$$

Among these, $OntologyVector$ represents the semantic vector of the referent domain, $MetaVector$ denotes the semantic vector of the metaphorical domain, $\cdot$ signifies the dot product of quantities, and $\|\cdot\|$ indicates the norm of the vector.

C. Fusion Analysis Module

Fusion analysis is a critical step in integrating the metaphorical meaning of poetry, aiming to decipher the cognitive logic behind metaphors and quantitatively assess the fusion effect of metaphorical meaning in the synthetic space. This study combines the deep semantic reasoning capabilities of the DeepSeek-R1 large model with Conceptual Integration theory to achieve fusion analysis.

DeepSeek-R1 is a large language model with powerful deep semantic reasoning capabilities. Through its multi-layer neural network architecture, it captures deep semantic features in text and demonstrates outstanding reasoning abilities across various complex tasks. In metaphor fusion analysis, DeepSeek-R1 is employed to deconstruct the cognitive logic underlying metaphors, reconstructing the transformation and restructuring of imagery schemas.

Based on conceptual integration theory, this study designed a fusion degree calculation algorithm to quantitatively evaluate the integration effectiveness of metaphorical meaning within the synthetic space. Specifically, semantic vectors from the ontology domain and metaphor domain are fused to generate semantic vectors in the synthetic space. Subsequently, similarity between the semantic vector in the synthetic space and the semantic vectors of the referent domain and metaphor domain is computed to evaluate integration effectiveness. Fig. 14 illustrates how the DeepSeek-R1 large model parses the cognitive logic behind metaphors and the integration degree calculation process based on conceptual integration theory, visually presenting the implementation path for metaphorical meaning integration.

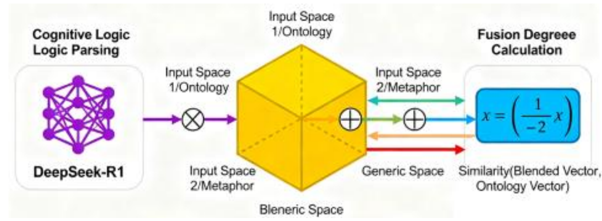

Fig. 14. DeepSeek-R1 inference and concept integration process.

D. Methodological Steps

In summary, the AI algorithm implementation path for integrating metaphorical meanings in poetry encompasses data preprocessing, metaphor identification, and fusion analysis. The workflow is illustrated in Fig. 15, with specific steps as follows:

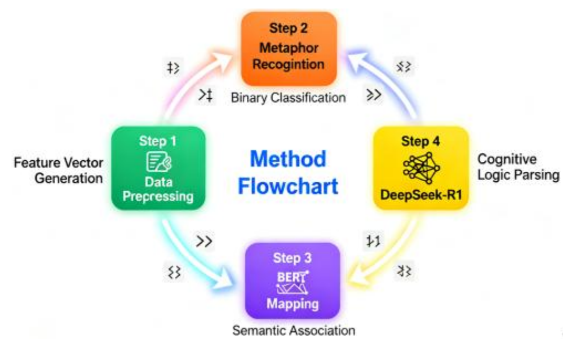

Fig. 15. Method flowchart.

Step 1: Data Preprocessing. Clean, annotate features, and convert formats of the online discourse poetry corpus to generate feature vectors suitable for model input.

Step 2: Metaphor Identification. Employ a hybrid SVM-CNN algorithm to achieve binary classification of "metaphorical sentences/non-metaphorical sentences" and subclassify metaphor types.

Step 3: Semantic Mapping. Construct semantic vector spaces for the referent domain and metaphor domain based on the BERT pre-trained model to quantify semantic association strength.

Step 4: Integration Analysis. Combine the DeepSeek-R1 large model with conceptual integration theory to decipher the cognitive logic behind metaphors and evaluate the effectiveness of metaphorical meaning integration.

V. Experimental Design and Effect Validation

A. Experimental Protocol Design

1) Experiment objectives and data collection: This experiment aims to validate the effectiveness and superiority of the proposed AI algorithm for integrating metaphorical meanings in poetry. By comparing different algorithms' performance in metaphor identification, semantic mapping, and fusion analysis tasks, it evaluates model accuracy and stability, providing a quantitative analytical method for poetry metaphor research.

The experimental dataset is sourced from the constructed online discourse poetry corpus, comprising 2,200 preprocessed poems. The dataset is divided into training, validation, and test sets at ratios of 70%, 10%, and 20%, respectively. Stratified random sampling is employed to ensure the proportion of metaphorical and non-metaphorical sentences in each subset aligns with the overall dataset.

2) Algorithm selection and parameter configuration: To validate the effectiveness and superiority of the proposed AI algorithm for integrating poetic metaphor meanings, comparative analysis was conducted using SVM, CNN, BERT pre-trained models, the DeepSeek-R1 large model, SVM+CNN fusion algorithms, and BERT+DeepSeek-R1 fusion algorithms. Specific parameter configurations are detailed in Table IV.

TABLE IV. ALGORITHM PARAMETER SETTINGS

No.	*Algorithm*	*Parameter settings*
1	SVM	Regularization parameter C set to 1.0, Kernel function set to radial basis function (RBF)
2	CNN	Two convolutional layers: First layer kernel size 3x3 filter count 64. Second layer kernel size 2x2 filter count 32. Pooling layer uses max pooling pooling window size 2x2. Fully connected layer neuron count 128 activation function ReLU
3	BERT	Using Transformer-based BERT-base model Hidden layer size 768, attention head count 12 Learning rate 2e-5, training epochs 3
4	DeepSeek-R1	Using medium model configuration of DeepSeek-R1 Multiple Transformer encoder layers, Temperature parameter set to 0.7

3) Experimental environment configuration: The experimental environment configuration comprises hardware setup and software environment. For hardware, the CPU is an Intel Core i7-10700K with a base frequency of 3.8GHz; the GPU is an NVIDIA GeForce RTX 3080 with 10GB of VRAM; and the memory consists of 32GB DDR4 RAM operating at 3200MHz. Regarding the software environment, the operating system is Windows 10 Professional 64-bit; the programming language is MATLAB 2021a; the deep learning framework utilizes the MATLAB Deep Learning Toolbox.

4) Training process parameters: During model training, the initial learning rate is set to 0.001 and adjusted using a cosine annealing strategy; the batch size is set to 32, adjusted based on the graphics memory capacity of the experimental equipment; the Adam optimizer is employed for its superior convergence performance; The number of training epochs was set to 20, dynamically adjusted based on model convergence.

5) Evaluation metrics: Metaphor recognition was evaluated using Precision, Recall, and F1 score. Precision measures the proportion of correctly identified metaphor sentences. Recall measures the proportion of all metaphor sentences correctly retrieved. F1 score is the harmonic mean of precision and recall, providing a comprehensive evaluation of model performance.

Semantic mapping calculates the correlation coefficient for semantic association strength, assessing semantic similarity between the ontology domain and metaphor domain.

Fusion analysis evaluates metaphorical meaning fusion effectiveness using mean fusion degree and standard deviation, where a higher fusion degree indicates better fusion quality.

B. Results Analysis

1) Data preprocessing results analysis: First, the online poetry corpus sourced from platforms such as poetry websites, forum comments, and social media shares underwent text cleaning. The results are shown in Table V. This table details the cleaning outcomes, reflecting the effectiveness of each step and the final corpus size. After cleaning, 2,200 high-quality poetry texts were retained.

TABLE V. TEXT CLEANING RESULTS TABLE

Cleaning step	*Initial corpus count*	*Corpus count after cleaning*	*Cleaning rate*
Removing irrelevant symbols	3000	2850	5
Removing duplicate content	2850	2500	12.28
Removing non-poetry text	2500	2200	12

Table VI summarizes the annotation results for metaphor-related vocabulary, including the number of words across different parts of speech and their proportion in the total vocabulary. Nouns, verbs, and adjectives play a significant role in metaphorical expressions, and the annotation of these words provides key features for subsequent metaphor recognition.

TABLE VI. STATISTICAL TABLE OF METAPHOR-RELATED VOCABULARY ANNOTATION

Part-of-speech type	*Number of words*	*Proportion in total vocabulary*
Nouns	5000	40
Verbs	3500	28
Adjectives	2500	20
Other	1500	12

Table VII summarizes the detailed results of data augmentation, reflecting the enhancement effects of each method and the final corpus size. Through data augmentation, the final corpus size increased from 2,200 to 5,500 poems, significantly improving the diversity and richness of the corpus.

TABLE VII. DATA AUGMENTATION RESULTS TABLE

Augmentation method	*Initial corpus count*	*Corpus count after augmentation*	*Augmentation rate*
Synonym replacement	2200	3300	50
Sentence reorganization	3300	4400	33.33
Sentiment reversal	4400	5500	25

2) Analysis of semantic fusion performance: To evaluate the effectiveness and superiority of the proposed AI algorithm for integrating poetic metaphor meanings, this section provides explanatory insights into metaphor recognition performance, semantic mapping capabilities, and fusion analysis abilities.

Table VIII presents a comparative analysis of metaphor recognition performance across different algorithms. Through three metrics—accuracy, recall, and F1 score—the classification effectiveness of each algorithm for metaphorical and non-metaphorical sentences can be comprehensively assessed. The data in the table demonstrates that the SVM+CNN fusion algorithm outperforms both standalone SVM and CNN algorithms in terms of accuracy, recall, and F1 score. This indicates that the fusion algorithm more effectively captures the features of metaphorical sentences, thereby enhancing recognition accuracy and stability.

TABLE VIII. COMPARISON OF METAPHOR RECOGNITION PERFORMANCE ACROSS DIFFERENT ALGORITHMS

Algorithm combination	*Accuracy percentage*	*Recall percentage*	*F1 score percentage*
SVM	85	80	82.4
CNN	83	82	82.5
SVM+CNN	87	85	86

Fig. 16 presents the comparative results of different algorithms within the metaphor recognition module. The horizontal axis represents various algorithms, including SVM, CNN, and the SVM-CNN hybrid algorithm; the vertical axis shows classification accuracy (%) on the left and recall (%) on the right. The figure reveals that the SVM-CNN fusion algorithm achieves 87% classification accuracy and 85% recall rate, outperforming both standalone SVM and CNN algorithms. This demonstrates that the fusion approach better captures the features of metaphorical sentences, thereby enhancing recognition performance. The differently colored bar charts represent the accuracy and recall rates of each algorithm, while the line charts illustrate the performance trends across different feature dimensions.

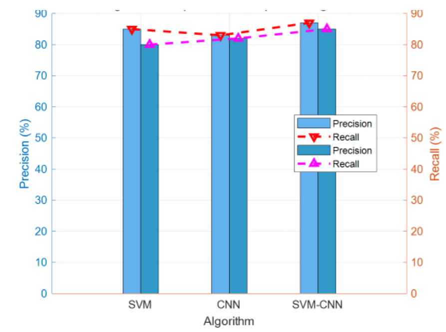

Fig. 16. Comparison of algorithms in the metaphor recognition module.

Fig. 17 illustrates the distribution characteristics of semantic association strength across five distinct poetry sample sets. The figure reveals that Sample Sets 3 and 5 exhibit overall higher semantic association strength, with medians approaching the upper limit and data points concentrated within a narrow range. This indicates that the metaphorical expressions within these two sample sets are semantically highly correlated, demonstrating consistent metaphorical quality and achieving elevated artistic and expressive effects. Sample set 2 exhibits relatively low semantic association intensity, with the box plot positioned lower and data distribution more dispersed. This indicates greater variation in metaphorical semantic connections within this set, suggesting that metaphorical expressions in some poems may lack clarity or depth, with room for improvement in artistic quality. Sample sets 1 and 4 exhibit moderate semantic association strength. Sample set 4 shows relatively concentrated data distribution, indicating superior stability in metaphorical semantic associations compared to sample set 1. Meanwhile, certain samples within sample set 1 demonstrate significantly higher semantic association strength than others, potentially signifying more refined metaphorical expressions or deeper semantic connections in these poems, highlighting their artistic merit. Additionally, the scatter plot uses distinct colors to mark the specific semantic association strength values for each poetry sample, allowing observation of each sample's unique characteristics.

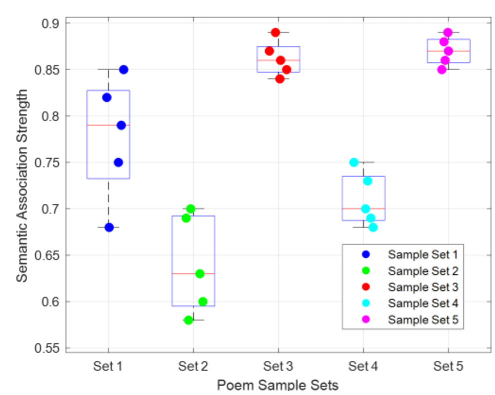

Fig. 17. Distribution of semantic association strength.

Table IX illustrates the relationship between semantic association strength and fusion degree across different samples, along with their calculated correlation coefficients. Semantic association strength reflects the degree of semantic similarity between the referent domain and the metaphorical domain, while fusion degree measures the integration effectiveness of metaphorical meaning within the synthetic space. The table reveals a high positive correlation between the two, with a correlation coefficient of 0.89. This indicates that stronger semantic association leads to better integration of metaphorical meaning. Consequently, constructing an accurate semantic vector space is crucial for achieving effective metaphorical meaning integration.

TABLE IX. CORRELATION ANALYSIS FOR SEMANTIC ASSOCIATION STRENGTH AND INTEGRATION DEGREE

No.	*Semantic association strength*	*Fusion degree*	*Correlation coefficient*
1	0.76	0.815	0.89
2	0.65	0.705	
3	0.83	0.8	
4	0.72	0.75	
5	0.88	0.84	

Fig. 18 illustrates the trend of metaphor fusion degree across varying parameters within the fusion analysis module. The horizontal axis represents parameters (such as window size and part-of-speech feature weights), while the vertical axis displays fusion degree values, utilizing a combination of a 3D line chart and a bubble chart. The 3D line chart vividly depicts the dynamic trajectory of fusion degree across multiple parameters, enabling clear observation of the combined effects of different parameter combinations on fusion performance. The bubble chart further emphasizes relative differences in fusion degree through bubble size, allowing more intuitive identification of the optimal parameter settings corresponding to the best fusion outcomes. This combined visualization comprehensively reveals the patterns of fusion degree variation under multi-parameter influence, aiding in model parameter optimization and enhancing metaphorical meaning fusion effectiveness.

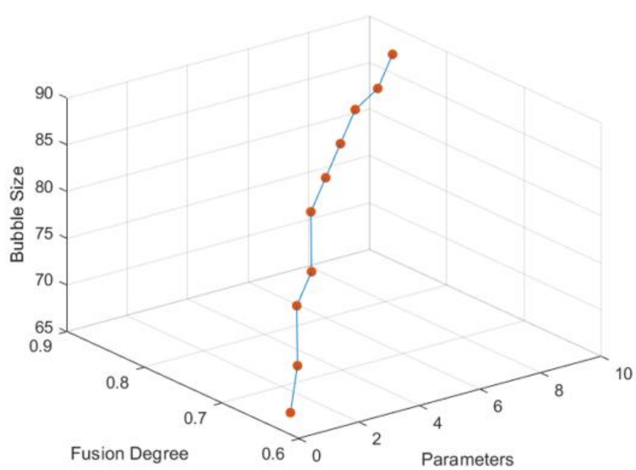

Fig. 18. Integration level variation with parameters.

Table X evaluates the integration effectiveness of metaphorical meanings across different poetic themes. The average integration level reflects the overall fusion quality of metaphorical meanings across all poetic themes, while the standard deviation indicates the dispersion of integration levels across individual samples. The table reveals that love-themed poetry exhibits the highest average integration degree with a relatively small standard deviation, indicating high stability and consistency in metaphor integration under this theme. Conversely, social-themed poetry demonstrates the lowest average integration degree with a relatively large standard deviation, suggesting significant variation in metaphor integration effectiveness.

TABLE X. METAPHOR INTEGRATION EFFECTIVENESS EVALUATION

Poetry theme	*Number of samples*	*Average fusion degree*	*Standard deviation*
Love	50	0.85	0.06
Nature	50	0.78	0.12
Life	50	0.82	0.08
Society	50	0.75	0.10

Table XI provides a comprehensive comparison of different model combinations across multiple evaluation metrics. Beyond focusing on metaphor recognition accuracy, metrics such as semantic association strength correlation coefficient, mean fusion degree, and training time are introduced to comprehensively assess model performance and practicality. The table reveals that the BERT model demonstrates superior performance in metaphor recognition accuracy, semantic association strength correlation coefficient, and mean fusion degree, though it requires relatively longer training time. In contrast, the SVM+CNN fusion algorithm maintains high recognition accuracy and fusion effectiveness while achieving relatively shorter training time, offering better balance and practicality.

TABLE XI. COMPREHENSIVE COMPARISON OF MODEL EVALUATION METRICS

Model combination	*Metaphor recognition accuracy percentage*	*Semantic association strength correlation coefficient*	*Average fusion degree*	*Training time minutes*
SVM	85	0.78	0.78	12
CNN	83	0.8	0.79	25
BERT	88	0.85	0.83	45
SVM+CNN	87	0.82	0.81	20

Fig. 19 shows the curve of loss function values during model training. The horizontal axis represents the number of training epochs, while the vertical axis denotes the loss function value. The figure reveals that as the number of training epochs increases, the loss function values of all models exhibit a decreasing trend. However, the rate of decrease and the final loss values differ among them. The BERT-based model demonstrates a faster rate of loss reduction and achieves a lower final loss value, indicating superior convergence during training and a more effective ability to learn patterns within the data.

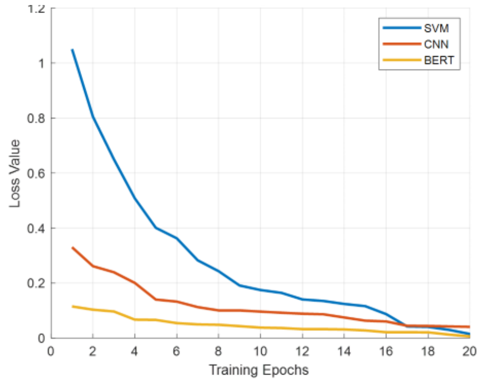

Fig. 19. Changes in model training loss function values.

Fig. 20 illustrates the performance metrics comparison of different algorithms in metaphor recognition tasks. The horizontal axis represents various algorithm combinations, while the vertical axes respectively denote accuracy (%), recall (%), and F1 score (%). By comparing the heights of different groups of histograms, one can intuitively observe the comprehensive performance of each algorithm in metaphor recognition tasks. The bar chart for the SVM-CNN fusion algorithm exhibits a higher overall height, indicating that this algorithm achieves a good balance across accuracy, recall, and F1 score, demonstrating superior metaphor recognition capability.

Fig. 21 compares the confusion matrices of different models on the metaphor recognition task. The horizontal and vertical axes represent predicted categories and true categories, respectively, including metaphorical sentences and non-metaphorical sentences. By comparing the confusion matrices of different models, one can intuitively observe the classification performance differences across categories. Deep learning-based models demonstrate high accuracy in classifying both metaphorical and non-metaphorical sentences. Their confusion matrices feature darker colors along the diagonal and lighter colors off-diagonally, indicating these models effectively distinguish between the two sample types and reduce misclassification rates.

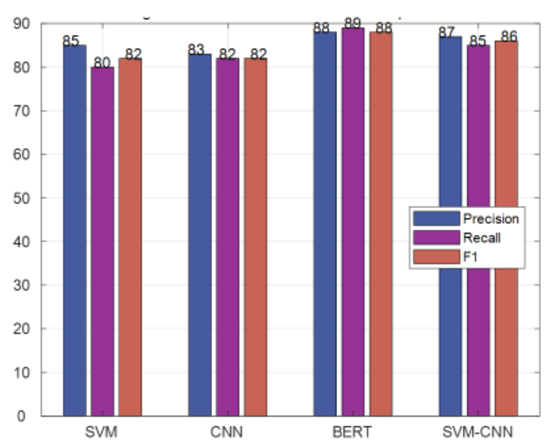

Fig. 20. Comparison of performance metrics across different algorithms.

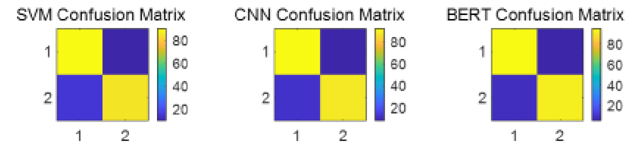

Fig. 21. .Confusion matrix comparison.

Fig. 22 illustrates the comparative fusion effectiveness of different poetic themes within the fusion analysis module. The horizontal axis represents poetic themes, while the vertical axis indicates fusion degree values. By comparing the positions and shapes of box plots across different themes, it is evident that love-themed poems exhibit a generally higher metaphorical fusion degree with a more concentrated distribution. This suggests that metaphorical meaning fusion within this theme demonstrates high stability and consistency. In contrast, nature-themed poems show a more dispersed fusion degree distribution, indicating that their metaphorical meaning fusion is influenced by multiple factors and exhibits significant variation.

Fig. 23 shows the learning rate curve during model training. The horizontal axis represents the number of training iterations, while the vertical axis displays the learning rate values, presented as a stem-and-leaf plot. This plot clearly illustrates the trajectory and distribution of the learning rate as training progresses. Initially, the learning rate is relatively high, gradually decreasing and stabilizing as training continues. This learning rate adjustment strategy facilitates rapid convergence during the early training phase while enabling fine-tuning of model parameters in later stages, thereby enhancing both training efficiency and generalization capabilities.

Fig. 24 presents a comparison of ROC curves and AUC values for different models on the metaphor recognition task. The horizontal axis represents the false positive rate, while the vertical axis denotes the true positive rate. The ROC curve of the SVM-CNN fusion algorithm lies near the upper-left corner, achieving an AUC value of 0.92. This indicates that the model demonstrates strong classification performance on the metaphor recognition task, effectively distinguishing metaphorical sentences from non-metaphorical ones.

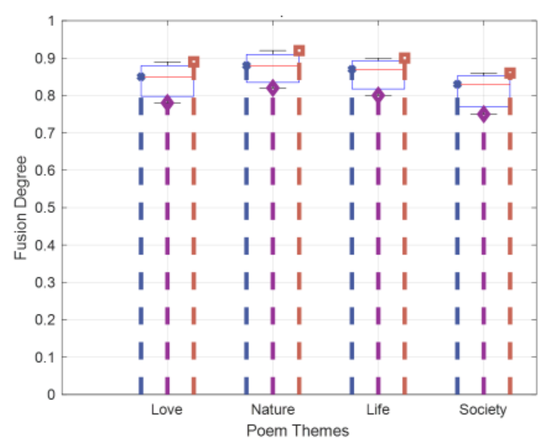

Fig. 22. Comparison of fusion effects across different themes.

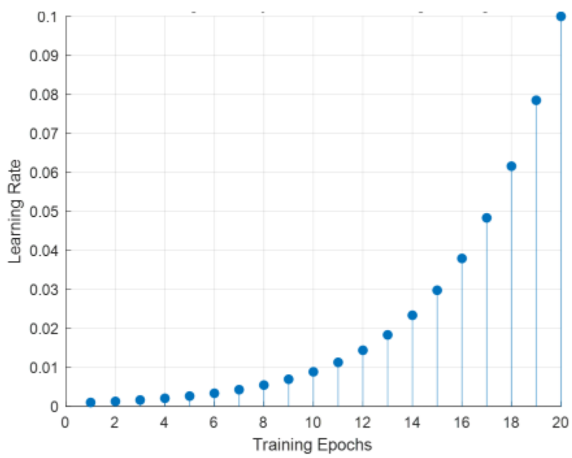

Fig. 23. Learning rate curve.

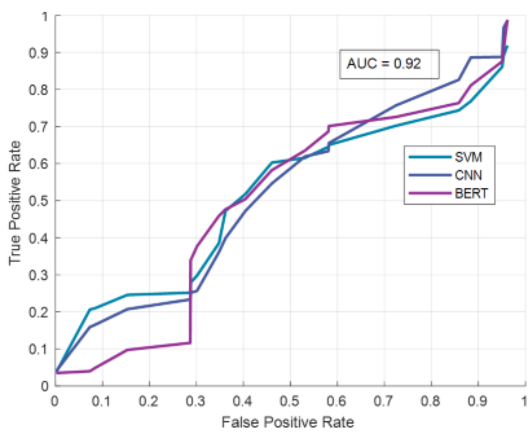

Fig. 24. Comparison of ROC curves and AUC values.

VI. CONCLUSION

This study proposes a fusion analysis framework for the metaphorical meaning of online poetry based on cognitive linguistics and Artificial Intelligence technologies, whose effectiveness is validated through detailed experiments. The designed three-dimensional fusion analysis framework—combining cognitive theory, specific AI algorithms, and online discourse data—achieves favorable results in both poetry metaphor recognition and semantic fusion. Experiments demonstrate that the SVM+CNN fusion algorithm exhibits high accuracy and recall in metaphor recognition tasks, effectively enhancing metaphor identification performance. The BERT model demonstrated robust contextual semantic encoding capabilities in the semantic mapping task, providing strong support for semantic analysis. The DeepSeek-R1 large model, combined with conceptual integration theory, performed excellently in metaphorical meaning fusion analysis, effectively deciphering the cognitive logic behind metaphors and quantifying fusion effects. Experimental results validated the effectiveness of the proposed framework and methods, demonstrating their potential in the field of poetic metaphor research.

Future work involves expanding and deepening the research. First, exploring the incorporation of multimodal data, such as audio recordings of poetry recitations and related visual materials, to enrich the analytical dimensions of metaphorical meaning integration in poetry. Second, further optimizing the algorithmic model by integrating cutting-edge technologies like the Transformer architecture to enhance the model's ability to recognize and understand complex metaphorical expressions.

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