Knowledge-Augmented Deep Learning Framework for Chinese Literary Text Analysis Using ARO-HA-BiLSTM

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Chinese literary texts spanning classical, modern, and contemporary periods present significant challenges for computational interpretation due to their deep semantic structures, metaphorical richness, and historical context. Traditional NLP approaches often fail to capture hierarchical narrative dependencies and culturally embedded meanings. This study proposes a Knowledge-Augmented Literary Text Analysis Framework that integrates ChatGLM-based knowledge-enriched embeddings with a Hierarchical Attention-based Bidirectional Long Short-Term Memory (HA-Bi-LSTM) network, optimized using the Adaptive Remora Optimization (ARO) algorithm. A corpus of 2000 Chinese literary texts was pre-processed using tokenization, rule-guided normalization, and structure-aware segmentation to preserve linguistic and contextual integrity. The proposed ARO-HA-BiLSTM model achieved an accuracy of 0.9724, precision of 0.9851, recall of 0.9718, and F1-score of 0.9734, outperforming existing models such as EL-GCN (accuracy 0.8855) and TextCNN (accuracy 0.8613). Ablation analysis further confirms the effectiveness of knowledge-enriched embeddings and adaptive hyperparameter optimization in enhancing semantic and thematic classification. The results demonstrate that integrating knowledge-augmented Chinese large language models with hierarchical deep learning significantly improves cross-era literary interpretation. This framework provides a robust computational methodology for digital humanities research and supports scalable, machine-assisted analysis of culturally rich literary corpora.

Povzetek: Študija predstavi znanjem podprt okvir za analizo kitajskih literarnih besedil, ki združi ChatGLM obogatene vgraditve s hierarhično-pozornostnim BiLSTM in ARO optimizacijo za natančnejšo semantično/tematsko klasifikacijo skozi različna zgodovinska obdobja.

1 Introduction

Traditional methods of analyzing Chinese literary texts do not meet the analytical capacity of the Chinese literary texts. Computational approaches to the analysis of Chinese Literary Texts have not captured the full complexity of China's literary history due to the presence of many levels of meaning. Current technological advancements in Deep Learning (DL) and language models (LMs) that utilize additional knowledge can serve as a better foundation for Chinese literary text analyses than previous methods [1]. These writings create an understanding of how Chinese society and thought evolved throughout history by illustrating the social and political landscape and providing insight into the thoughts and experiences of individuals [2]. There are a variety of semantic structures, rhetorical devices, and cultural symbols used in the Chinese literary works. They could be integrated to understand the development of language over centuries and how ideas are shared through time [3]. The semantic features found in early Chinese poetry and prose demonstrate the art of language and the emotional and social state of the time period; they could provide key insights for both Humanities researchers and computational modeling in Linguistics [4]. The ability to perform advanced Natural Language Processing (NLP) on a large scale allows researchers to correlate a wide variety of different Chinese literary works and create quantitative models for the development of literary heritage and cultural knowledge from historical contexts [5]. Traditional NLP approaches are limited when applied to literary interpretation. The earliest models developed in NLP, including bag-of-words and basic topic models, have difficulty in modeling deep semantic meaning, rhetorical devices, and narrative subtext in literature, resulting in superficial or false analytical results [6, 7]. Traditional sentiment analysis (SA) models cannot recognise complex emotional patterns and cultural symbols that are present in much literature [8]. Even transformer-based summary systems produce summaries that frequently do not preserve or misrepresent authorial intent or thematic nuance. These limitations present a need for contextually-aware, culturally sensitive, and semantically rich models for computational literary research [9,10]. Many current text mining systems and NLP techniques depend on simple pattern recognition and statistical associations. They are unable to provide in-depth semantic understanding of complex meanings and narrative structures present within the texts analysed [11]. This is true when dealing with culturally oriented content, as many models used today tend to represent idiomatic phrases, metaphors, and culturally specific expressions poorly in their embeddings [12]. The training data sets used to train traditional NLP systems make it difficult for these systems to develop broader contextual models that take into account the nuanced linguistic and cultural factors that affect complex interpretation tasks [13]. The majority of the LMs used are not able to account for cultural bias or perform as accurately regarding material written outside the dominant training distributions, leading to significant misrepresentation of contextually rich texts [14]. This shows a need for progress in computational approaches based upon culturally aware and more semantically rich representations of literature and the humanities [15]. Figure 1 outlines the application of Knowledge Augmented DL in generating insights from classical/modern/contemporary Chinese literature by combining literary text, available Knowledge Resources, and DL analysis to enhance semantic, thematic, and emotional comprehension.

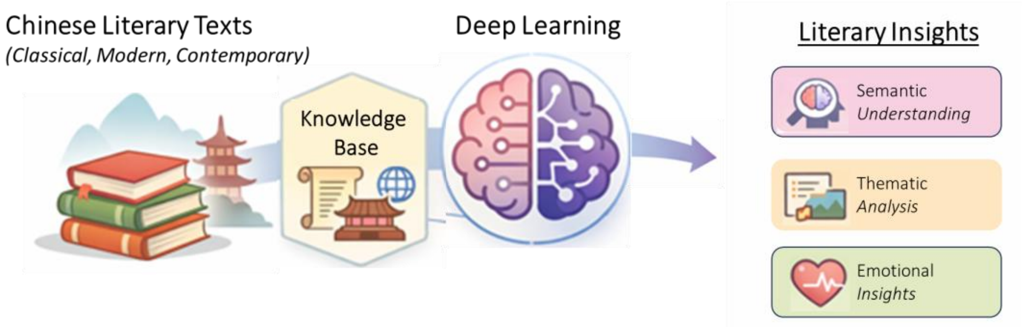

Figure 1: Conceptual overview of DL-assisted literary text analysis

1.1 Research objectives and questions

The primary objective of this research is to develop a knowledge-augmented DL framework capable of performing hierarchical and semantically enriched analysis of cross-era Chinese literary texts. The research attempts to build an ARO-HA-BiLSTM model that enhances automatic interpretation of Chinese literary text across classical, modern, and contemporary periods. To achieve this objective, the research addresses the following research questions:

RQ1: Can knowledge-augmented embeddings generated using ChatGLM improve semantic depth and contextual understanding in cross-era Chinese literary text analysis compared to conventional deep learning approaches?

RQ2: Does the integration of hierarchical attention-based BiLSTM with ARO significantly enhance thematic coherence, sentiment classification accuracy, and convergence stability in literary text modeling?

1.2 Key contribution

- A novel knowledge-augmented literary analysis framework integrating large-scale Chinese language modeling with structured linguistic, cultural, and historical ontologies to enhance contextual depth in cross-era text interpretation.
- A hierarchical attention-based BiLSTM architecture specifically adapted to capture narrative-level semantic dependencies and metaphorical structures in Chinese literary texts.
- The first application of Adaptive Remora Optimization (ARO) for deep semantic literary modeling significantly improved convergence stability and classification consistency.
- A statistically validated evaluation across thematic (nature, love, heroism) and sentiment (positive, neutral, negative) dimensions demonstrating robust and reproducible performance improvements over existing deep learning baselines.

2 Related works

The challenge of analyzing large volumes of Chinese modern and contemporary literary texts was addressed by utilizing a method for thematic clustering and text mining [16]. Results showed that the method significantly improved clustering efficiency and stability with fewer keywords, though it was limited to the effectiveness of selected keyword-based techniques. The research trends in text sentiment analysis (SA) were explored by suggesting a topic discovery model [17]. Analysis of 1,186 articles from 2012 to 2022 revealed 12 topic categories, highlighting trends such as the popularity of social media opinion analysis, the need for method integration, challenges in aspect-level semantic disambiguation, and the importance of multimodal sentiment research. It was limited by its reliance on keyword-based clustering and literature from selected databases. The author of [18] emphasized the importance of lightweight, efficient computational frameworks for large-scale intelligent systems. For instance, a hash-based Message Authentication Code (HMAC) -based token authentication protocol with Bloom filter–based revocation was proposed for fog-assisted vehicular networks, achieving secure mutual authentication with significantly reduced computational and communication overhead. The framework demonstrates how knowledge-aware design and lightweight optimization can improve scalability, efficiency, and robustness in complex, real-time environments. Such approaches highlight the value of integrating structured mechanisms with computational intelligence to enhance performance under resource constraints. The text SA was improved by utilizing Machine Learning (ML) through a novel weight-distributing method [19]. Empirical results showed that it attained an accuracy of 0.821, demonstrating enhanced effectiveness in sentiment classification. But it relies on predefined sentiment dictionaries and vector representations. The SA of Chinese subjective texts was improved for mental health applications by integrating Ernie-Tiny embeddings with Bidirectional Gradient Recurrent Unit (BiGRU) for semantic feature representation and sentiment classification [20]. Experiments on datasets showed that the model achieved higher accuracy (84.30%), precision (83.95%), recall (88.35%), and F1-score (85.98%). The approach was limited by potential challenges in handling extremely short or highly ambiguous texts and dependence on platform-specific datasets. However, its lightweight architecture limits its ability to model complex hierarchical and cross-era literary semantics. Table 1 shows the purpose of evaluating the automation of large volumes of texts. It develops a better understanding of what these texts were saying through summarisation and sentiment extraction, and compares each of the methods used for evaluation and lists their limitations, identifying the research gaps.

Table 1: Comparison of text summarization and SA techniques in literary and large-scale textual data

Ref	Task Focus	Key Technique / Model	Data / Domain	Performance Highlights	Limitations
[21]	Literary sentiment and theme extraction.	BiLSTM + Attention with Improved Particle Swarm Optimization (IPSO).	500 English novels.	High Accuracy and F1, outperformed a convolutional neural network (CNN).	Limited to English novels; scalability to larger corpora not validated.
[22]	Abstractive summarization.	Abstract Meaning Representation (AMR)-based Semantic Graph + DL.	Benchmark datasets.	Promising robustness and coherence.	High computational complexity.
[23]	Extractive summarization.	Knowledge-Enhanced Transformer + Graph Neural Network (GNN) (KETGS).	General documents.	Improved relevance and cohesion.	Graph construction overhead; domain adaptability not explored.
[24]	Abstractive summarization.	Bi-directional and Auto-Regressive Transformers (BART), Pre-training with Extracted Gap-sentences for Abstractive Summarization (PEGASUS)	Public datasets.	Improved Recall-Oriented Understudy for Gisting Evaluation (ROUGE) and Bilingual Evaluation Understudy (BLEU).	Depends heavily on large pretrained models.
[25]	Extractive & multi-document summarization.	Bidirectional Encoder Representations from Transformers + Latent Dirichlet Allocation + Graph Attention Network + Term Frequency–Inverse Document Frequency (BERT + LDA + GAT + TF-IDF).	CNN, Multi-News.	Superior ROUGE scores.	Increased model complexity; topic coherence varies across domains.

[26]	Extractive summarization.	GNN + GAT.	CNN, The New York Times (NYT).	Outperformed baseline extractive models.	Performance degrades on long documents.
[27]	Abstractive summarization.	Deep Reinforcement Learning (DRL) with semantic reward.	Turkish datasets.	Better alignment with human judgment.	Language-specific training limits cross-lingual generalization.
[28]	Extractive summarization.	SqueezeBERTSum.	General datasets.	98% BERTSum performance with fewer parameters.	Slight loss in expressiveness for complex summaries.
[29]	SA (classical Chinese).	BERT+Lexicon+GAT.	Classical Chinese literature.	Accuracy up to 95%.	Relies on lexicon quality; limited interpretability of clustering
[30]	SA (classical literature).	Ensemble-Graph Convolutional Network (EL-GCN).	Multi-era classics.	Accuracy 93.7%.	High computational cost; ensemble design complexity.

2.1 Research gaps and motivation

Existing computational literary analysis approaches primarily rely on lightweight transformer variants or conventional recurrent architectures that focus on short-text sentiment classification rather than hierarchical narrative modeling. These approaches lack integration of structured cultural and historical knowledge, limiting their ability to capture cross-era semantic evolution, metaphorical expression, and contextual nuance in Chinese literature. Furthermore, optimization strategies specifically tailored for literary semantic modeling remain underexplored, leading to convergence instability and reduced interpretability in deep architectures. To address these limitations, the proposed framework integrates knowledge-augmented ChatGLM embeddings with hierarchical attention modeling and ARO-based optimization, providing a unified and task-specific solution for cross-era Chinese literary interpretation.

3 Methodology

The systematic method explained in this section enables increased semantic comprehension, improved semantic understanding, and emotional interpretation through the use of Chinese literature. The methodology workflow, as demonstrated in Figure 2, is an effective combination of knowledge augmentation, DL semantics, and optimization to handle the complexities of culture and context regarding literary works across different eras.

3.1 Chinese literary text analysis dataset description

The dataset sourced from the Kaggle open site [31] contains a collection of 2000 texts of literature from

China's classical, modern, and contemporary era across a variety of genre types, including poetry, fiction, and essay format. Each text has been broken down into single sentences and tokens, with each sentence having information on the theme, sentiment polarity, and metaphor classification for that particular piece. To incorporate cultural and historical understanding, this dataset contains links between people, dynasties, and events on these themes and how they relate to each other for use in contextual semantics and for conducting thematic classifications, SA, and cross-era comparisons of the literature coming from China.

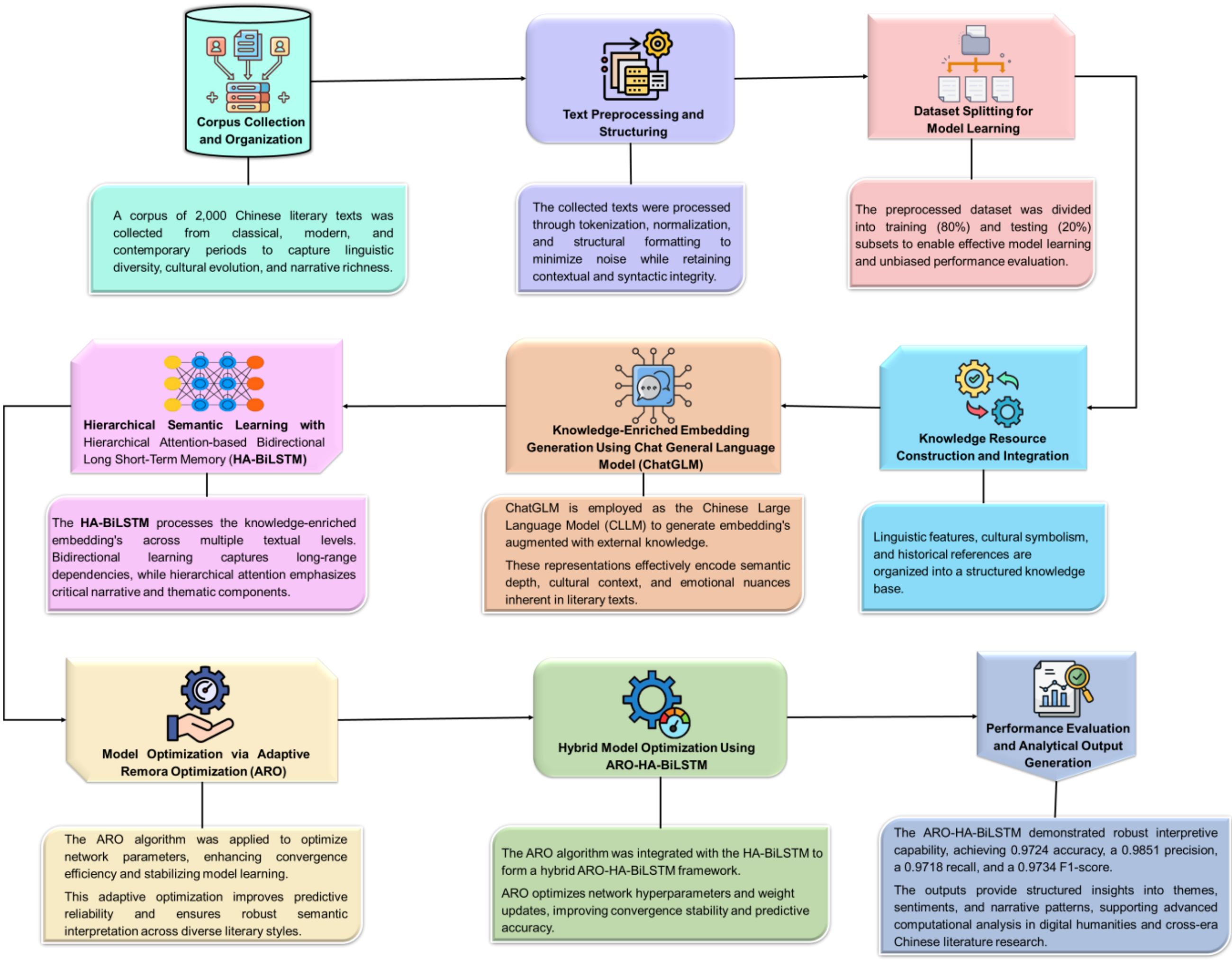

Figure 2: Knowledge-augmented semantic and thematic analysis workflow for Chinese literary works

3.2 Knowledge-augmented data pre-processing for Chinese literary text analysis

Multi-era Chinese literary works have been formatted through data pre-processing so that they can be analyzed by systems designed to learn deep semantic knowledge. The original linguistic structure, cultural context, and narrative flow from classical, modern, and current periods are preserved. The methods of processing included Chinese-specific tokenization, lexicon, and rule-guided normalization. Various types of information related to semantic meaning, thematic content, and emotional tone are maintained through the use of structure-aware pre-processing, enabling compatibility with knowledge-enriched embeddings and the hierarchical attention mechanisms utilized in the ARO-HA-BiLSTM framework.

➢ **Cross-era Chinese literary tokenization**

Tokenization is conducted with a focus on breaking down Chinese literature into segments that are both legible and meaningful to the reader and retaining the overall narrative coherence and linguistic structure of the work through the various periods of Chinese literature, from ancient to the present day. The culturally significant phrases, metaphors, and proper nouns are used in the literature because they are retained carefully as they are significant in discerning the meaning and sentiment of a work. Tokenized sequences created through this process represent a consistent, structured method for constructing knowledge-enriched embeddings, hierarchical models of the work, and performing accurate analysis of its theme and sentiment.

➢ **Rule-guided knowledge-aware normalization for Chinese literary texts**

The normalization method consists of three modules: the first module contains character-level standardisation using reliable Chinese conversion dictionaries, instead of simply replacing the traditional version with the simplified version; the second module contains an era awareness module that connects synonyms between ancient and modern Chinese through the curation of a cultural lexicon by using documented historical ontologies, such as dynasties, philosophies, literary schools; and the third module filters out non-semantic tokens to preserve poetry, rhyme, metaphorical and culturally-specific language or expressions by using a knowledge-based validation method to constrain normalization.

➢ Structure-aware pre-processing for hierarchical literary representation

The purpose of structural pre-processing is to preserve the inherent structural organization of Chinese literature throughout the classical, modern, and contemporary periods of history by breaking the text into smaller components like words, sentences, and blocks of discourse. The process of structural pre-processing creates an index for narrative structures, theme-related markers, and other elements important in understanding how the text is presented to its intended reader. The information about the entities and themes occurring in each segment of the narrative is stored in such a way as to provide continuity and coherence between text segments through time and across cultural contexts. This structuring of a narrative enables the user to derive knowledge enrichment through using hierarchical relationships and allows a better understanding when it comes time to interpret themes and sentiments in later stages of analysis.

3.3 Knowledge resource construction for context-aware literary interpretation

Using a combination of linguistic structure, cultural heritage, and historical knowledge related to the Chinese literary tradition, a structured knowledge resource is created to provide a context for understanding textual elements in their proper context. Implicit meaning, metaphor, and era-specific expression can be systematically arranged and understood based on the way they are used. By incorporating outside knowledge into the analysis of text, the deeper semantic relationships and thematic coherence of the textual representation are identified, providing a basis for an in-depth automated interpretation of the literature.

3.4 Knowledge-enriched embeddings using chatGLM for hierarchical literary text analysis

Although lightweight models such as Ernie-Tiny have demonstrated effectiveness in domain-specific sentiment analysis, they are primarily optimized for short-text classification and constrained semantic tasks. In contrast, ChatGLM is a large-scale Chinese language model trained on extensive corpora encompassing diverse linguistic, cultural, and historical contexts. This broader pre-training enables richer contextual representation, better handling of metaphorical expressions, and improved modeling of long-range narrative dependencies, which are critical in cross-era Chinese literary interpretation. Therefore, ChatGLM was selected as the embedding backbone to enhance semantic depth and contextual awareness within the proposed framework. In the ARO-HA-BiLSTM architecture, ChatGLM acts as the primary CLLM and provides a mechanism for generating knowledge-augmented embeddings that encompass linguistic, cultural, and historical contexts derived from a wide variety of Chinese literary training corpora from all time periods, including classical through modern to present. These knowledge-augmented embeddings provide a structure for preserving multiple levels of complexity of the semantic relationship between words and sentences and other larger forms of discourse structures, while maintaining their local lexical meanings and global contextual significance. The HA-BiLSTM network can better model the hierarchical structures of narratives by using the enriched knowledge contained within these embeddings. As the ChatGLM contain rich, contextualized knowledge about the meaning of literary devices, figurative language, and culturally specific references within Chinese Literature, incorporating a CLLM that is augmented with such knowledge would allow the HA-BiLSTM network the capability of building robust thematic relationships, detecting sentiment polarity, and recognizing subtle emotional nuances found in Chinese literature across multiple literary eras, by enabling more accurate machine-assisted scholarly interpretation of Chinese literature.

3.5 ARO-HA-BiLSTM for semantic, thematic, and emotional analysis of Chinese literary texts

The HA-Bi-LSTM captures word and sentence-level semantics by modelling the hierarchical narrative structure of Chinese literary works, using bi-directional sequence learning and attention mechanisms. Dynamically, ARO is applied to tune the network hyperparameters to have greater stability and reliability in the rate of convergence and interpretative accuracy. The ARO-HA-Bi-LSTM framework improves the ability to understand a literary text's meaning that establishes the theme or main idea, and gains an appreciation for the emotional nuance contained within each literary work.

➢ HA-BiLSTM for deep semantic learning for Chinese literary text analysis

The HA-BiLSTM in the analysis of Chinese literary texts determines how to model their hierarchy and sequence nature. By learning the relationships between words, the model captures the multi-level dependency between words and their context, thus enabling a deeper understanding of the emotions expressed at the word level, while providing context at the thematic level for effective knowledge-enhanced literary text analysis. There are six components of the HA-BiLSTM model to derive the semantic theme and sentiment from Chinese Literary Texts, including the text encoding layer, knowledge-enriched embedding layer, contextualised bi-directional narratives layer, literary-aware attentional layer, thematic and sentimental classification layer, and hierarchically narrative modelling layer. These layers provide a cohesive semantic theme and sentiment derived from Chinese literary texts, using a combination of cultural and contextual knowledge to enhance the text analysis. Figure 3 presents the HA-BiLSTM architecture with knowledge-enriched embeddings and narrative-aware attention to model themes and sentiment in Chinese literary works.

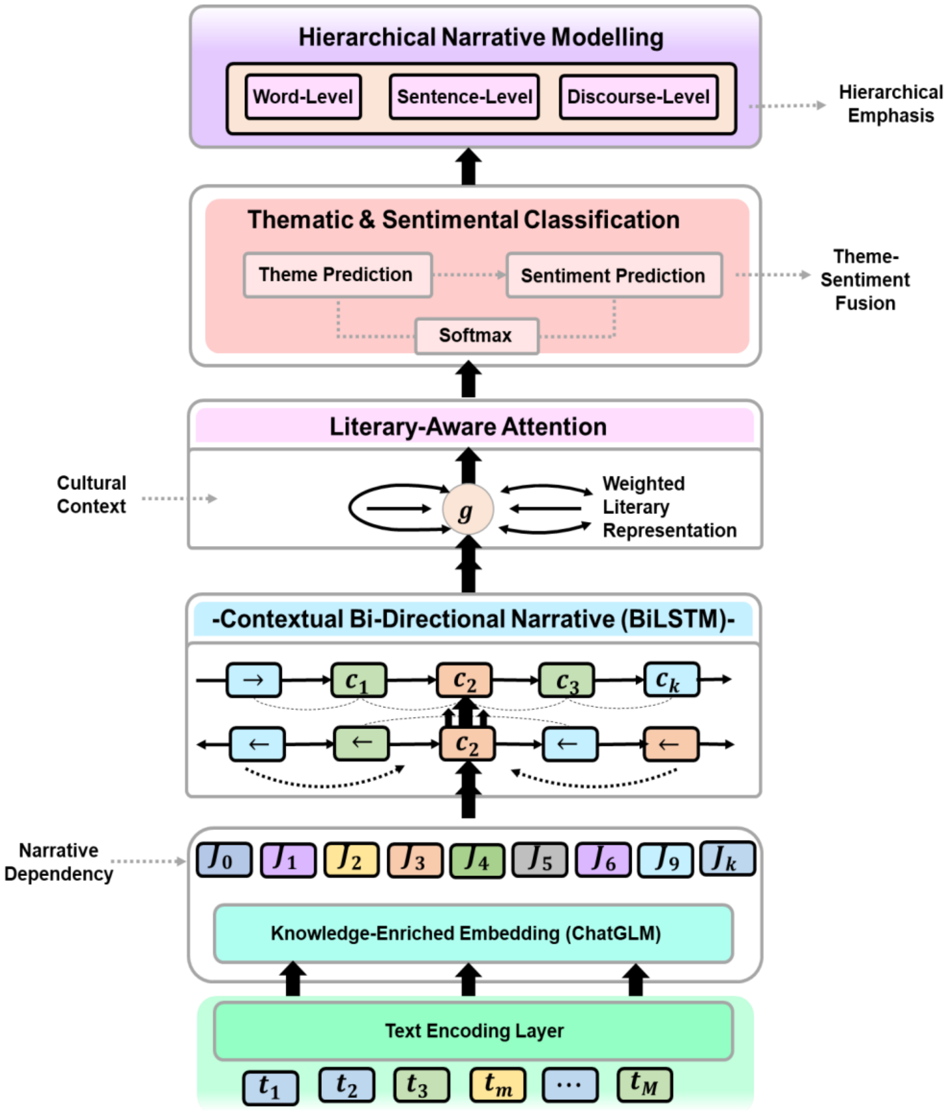

Figure 3: HA-BiLSTM architectural framework for knowledge-driven Chinese literary analysis

Text Encoding Layer: It accepts Chinese literary sentences that have been tokenized and position-marked as its input. This would produce an encoded representation of the entities, themes, and narrative markers to assist in maintaining the structural and contextual information of the Chinese literary text, which is essential for the subsequent knowledge-enriched embedding and SA.

Knowledge-Enriched Embedding Layer: Each token t_k in a sentence $L = t_1, t_2, \dots t_M$ is mapped to a knowledge-enriched vector J_k using Equation (1).

$$J_k = Q.u_k \quad (1)$$

Here, Q denotes the knowledge-augmented embedding matrix generated from ChatGLM, and u_k is the encoded vector of token t_k, and $t_1, t_2, \dots, t_M$ are the sequence of token representations corresponding to the text segment, where M is the total count of the tokens in the literary work after the pre-processing. This layer captures both lexical semantics and culturally-informed contextual knowledge.

Contextual Bi-Directional Narrative Layer: Knowledge-aware embeddings c_k are sent through a bi-directional recurrent architecture to discover the contextual dependencies between the preceding and succeeding text units using Equation (2).

$$c_k = [\overrightarrow{c_k} \| \overleftarrow{c_k}] \quad (2)$$

Here, $\overrightarrow{c_k}$ and $\overleftarrow{c_k}$ denote the historical narrative context and subsequent thematic context of the k^{th} textual unit, and $\|$ indicate the contextual fusion. Through the bidirectional semantic flow and hierarchical narrative development created by this layer, the model captures the long-term thematic continuity and evolution of sentiment within a body of literature.

Literary-Aware Attention Layer: By employing a multi-tiered attention mechanism, it allows for focusing upon both narrative and culturally meaningful characteristics of Chinese literature through the construction of the knowledge-based literary representation g. This layer applies dynamic weights, based on semantic contribution and contextual relevance, to textual components, as in Equations (3-5).

$$U = \tanh(C) \quad (3)$$
$$\beta = \mathrm{softmax}(\theta^{\top}C) \quad (4)$$
$$g = C\beta^{\top} \quad (5)$$

Here, C represents the sequence of context-enriched narrative states, U is the non-linearly transformed narrative features, $\theta^{\top}$ denotes the transpose of the learnable literary relevance vector, β and $\beta^{\top}$ represent the relative interpretive importance of each narrative unit and its transpose, and $\mathrm{softmax}(\theta^{\top}C)$ computes a normalized attention distribution. On combining weighted narrative cues.

Thematic and Sentimental Classification Layer: It changes the final learning predictions of literary themes and sentiment polarities into a predictive hierarchy based on collectively attended to features initially established and enriched with knowledge sources. A fully connected transformation using a softmax function is used to obtain estimations of class probabilities related to the semantic and emotional objectives. Model optimization based on categorical cross-entropy loss improves the accuracy of classifications from various types of literary texts. The dropout and L2 regularization techniques are applied for improving the generalizability and preventing over-fitting on the literary corpus of multiple Chinese eras.

Hierarchically Narrative Modelling Layer: It organizes the hierarchical structure of Chinese Literature by aggregating semantics from all three levels of language, including word, sentence, and discourse. First, a single set of weights provides a word-level representations that are combined to create a sentence's word embeddings that reflect local semantic or emotional cues; then, the sentence's word representations are further aggregated to create a paragraph or document's paragraph semantic or emotional themes; and finally, through explicit, structured hierarchical level learning across all three levels, this provides the ability to represent, model and capture long range dependencies, thematic coherence and implicit emotional shifts associated with traditional, modern and contemporary Chinese literature in this hierarchical narrative layer.

➢ Model optimization for enhanced semantic and thematic analysis using the ARO

The ARO algorithm is used to optimise the HA-BiLSTM network for improved interpretative performance of Chinese literary texts, and the flow is presented in Figure 4. The optimiser's intended outcome is to provide improved semantic representations, thematic clustering, and sentiment recognition through tuning of the model's hyperparameters. The ARO is a bio-inspired metaheuristic based on the evolutionary model of the Remora Fish's parasitic behaviour and foraging behaviour. The hyperparameter setting of the HA-BiLSTM model represents the generation of different configurations of parameters to achieve improved interpretive performance.

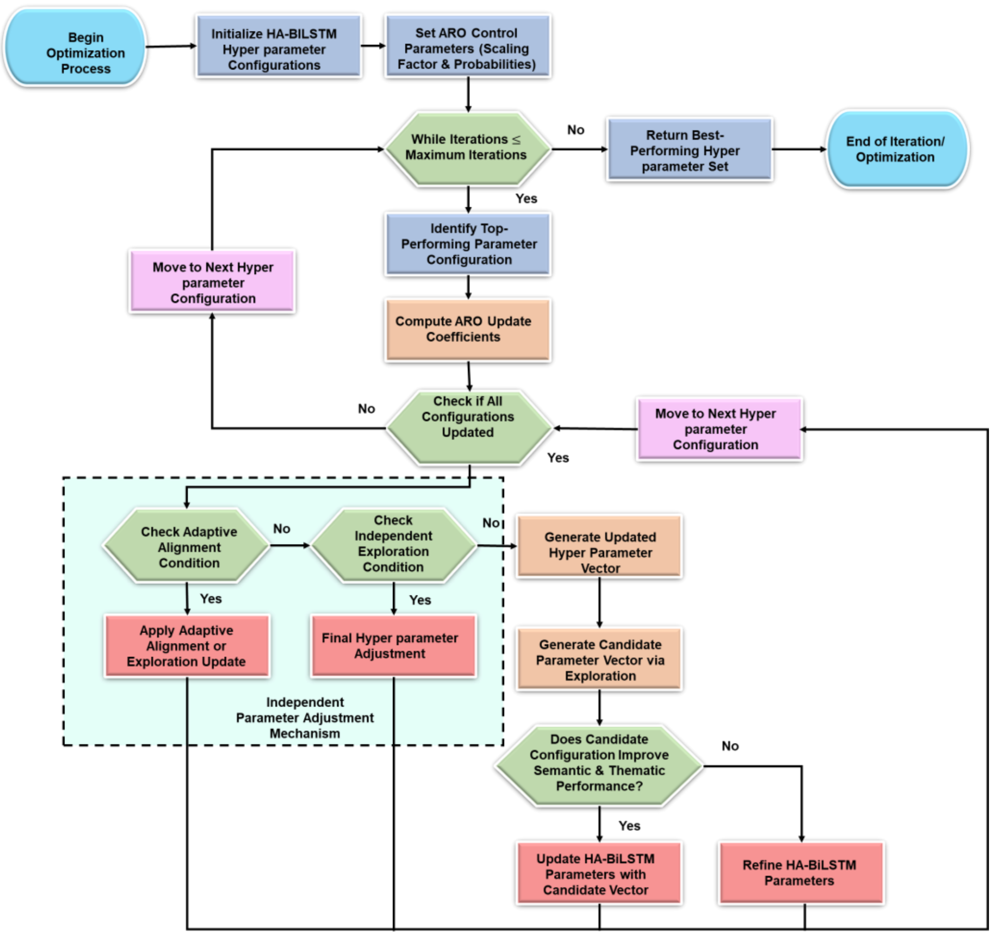

Figure 4: ARO-based hyperparameter optimization workflow for Chinese literary text analysis

Hyperparameter Exploration for Semantic Learning: To support the HA-BiLSTM network in developing better interpretive performance by interpreting semantic meaning, thematic coherence, and emotional nuance from Chinese literary texts effectively, parameter settings are created by exploring the wide variety of hyperparameter settings using Equation (6).

$$P_k^{l+1} = P_{min} + (P_{max} - P_{min}).q \quad (6)$$

Here, P_k^{l+1} is the updated HA-BiLSTM parameter configuration for the k^{th} instance at iteration $l+1$, P_{max} and P_{min} are the largest and smallest allowable values for each hyperparameter, and q denotes the random number $(0-1)$. This creates the opportunity for ARO to evaluate many different types of semantically and narratively derived features that are extracted from the corpus of texts.

Targeted Hyperparameter Optimization for Enhanced Semantic and Emotional Modeling: The ARO algorithm adapts and updates each parameter setting of the HA-BiLSTM network such that they increase their ability to converge on the highest-performing hyperparameter set to achieve improved interpretive performance, as in Equation (7), when interpreting thematic structure, semantics, and emotional nuance from Chinese literary texts.

$$P_k^{l+1} = \begin{cases} \frac{P_k^l}{1+\alpha}\left(P_{best}^l - P_k^l\right), & q < 0.5 \\ P_k^l.(1+\alpha).\left(P_{best}^l - P_k^l\right), & q \geq 0.5 \end{cases} \quad (7)$$

Here, P_k^l is the current HA-BiLSTM parameter configuration for the k^{th} instance at iteration l, P_{best}^l represents the parameter configuration yielding the highest thematic clustering and sentiment prediction accuracy in the current iteration, and α is an adaptive factor.

Stochastic Hyperparameter Diversification for Robust Literary Feature Learning: To avoid sub-optimal semantic or thematic representations in the HA-BiLSTM network, Levy-flight dynamics are used to provide stochastic perturbations to hyperparameters and diversify the configuration space, thereby allowing the network to explore the full range of potential configurations to improve the semantic understanding, thematic coherence, and emotional nuance of Chinese literary texts using Equation (8).

$$P_k^{l+1} = P_k^{l+1} + \beta.L(\sigma) \quad (8)$$

Here, $L(\sigma)$ increases the diversity of hyperparameter exploration, and β is a scaling factor.

Adaptive Hyperparameter Alignment for Optimized Literary Interpretation: After conducting exploratory tuning and stochastic diversification of each HA-BiLSTM parameter configuration, the configuration's parameters are adaptively aligned with the best-performing hyperparameter sets. This process facilitates convergence of the network to represent the semantic relationships, thematic coherence, and emotional nuances of Chinese literary texts, allowing a reliable and nuanced analysis of literature using Equation (9).

$$P_k^{l+1} = P_k^{l+1} + \gamma.\left(P_{best}^l - P_k^l\right) \quad (9)$$

Here, γ regulates convergence speed toward the optimal HA-BiLSTM configuration. By providing independent hyperparameter exploration, guided refinement, stochastic diversification, and adaptive alignment, ARO provides a mechanism for optimizing HA-BiLSTM parameters for literary text analysis. With the addition of knowledge-enhanced embeddings through the ChatGLM model, the optimized network yields an improved performance in semantic understanding, thematic clustering, and sentiment identification, resulting in a reliable and nuanced interpretation of classical, modern, and contemporary Chinese literary texts.

Algorithm 1: ARO-HA-BiLSTM Framework for Knowledge-Driven Chinese Literary Text Analysis

Begin

1. *TextEncodingandKnowledgeEnrichment*
   - *Tokenizeeach literarytextintot*$_1$,t_2,…,t_M
   - *Generateencodedvectorsu*$_K$
   - *Computeknowledge-enrichedembeddingsusingChatGLM*:

$$J_k = Q \cdot u_k$$

2. *ContextualBi-DirectionalNarrativeModeling*
   - *PassembeddingsthroughBiLSTMtoobtain*:

$$c_k = [(c_k)^{\rightarrow} \| (c_k)^{\leftarrow}]$$

3. *Literary-AwareAttentionMechanism*
   - *Computetransformednarrativefeatures*:

$$U = tanh \quad (C)$$

   - *Computeattentionweights*:

$$\beta = \text{softmax}(\theta^{\top} C)$$

   - *Generateliteraryrepresentation*:

$$g = C\beta^{\top}$$

4. *HierarchicalNarrativeAggregation*
   - *Aggregateword-level*, *sentence-level*, *anddiscourse-levelrepresentations*
   - *Producesemanticthemesandsentimentrepresentations*
5. *InitializeAROHyperparameterConfigurations*
   - *Foreach instancek*, *initialize*:

$$P_k^{l+1}=P_{min}+(P_{max}-P_{min})\cdot q$$

6. *Foreachiterationl*

7. *HyperparameterExplorationforSemanticLearning*

- *Updateconfigurationsusing*:

$$P_k^{l+1}=P_{min}+(P_{max}-P_{min})\cdot q$$

8. *TargetedHyperparameterOptimization*

- *Refineconfigurationstowardthebest-performingset*:

$$P_k^{l+1}=\begin{cases}\frac{P_k^l}{1+\alpha}(P_{best}^l-P_k^l), & q<0.5\\ P_k^l(1+\alpha)(P_{best}^l-P_k^l), & q\geq 0.5\end{cases}$$

9. *StochasticHyperparameterDiversification*

- *ApplyLevy-flightperturbation*:

$$P_k^{l+1}=P_k^{l+1}+\beta\cdot L(\sigma)$$

10. *AdaptiveHyperparameterAlignment*

- *Alignwith the bestconfiguration*:

$$P_k^{l+1}=P_k^{l+1}+\gamma(P_{best}^l-P_k^l)$$

11. *TrainHA-BiLSTMwithUpdatedParameters*

- *Performsemanticthemeandsentimentclassification*
- *Evaluateinterpretiveperformance*

12. *EndFor*
13. *FinalModelConstruction*

- *Select* P_{best}
- *OutputoptimizedARO-HA-BiLSTMmodel*

Algorithm 1 showed that, by integrating hierarchical narrative modeling and adaptive hyperparameter optimization, the ARO-HA-BiLSTM algorithm enhances the quality of interpretive analysis of Chinese literary works regarding semantic understanding, thematic consistency, and emotional analysis through the use of both techniques. The HA-BiLSTM model captures both narrative and contextual dependencies, while ARO provides stability in convergence and increased accuracy of interpretation. Table 2 provides an overview of key controllable factors related to the HA-BiLSTM model's parameters and the ARO algorithms. Through systematic adjustments of these hyperparameters, a stable convergence is obtained along with improved accuracy in interpreting texts, and through using knowledge-based enhancements to models that are developed from various data sources, including both classical and modern literature.

Table 2: Hyper-parameter tuning settings for the ARO-HA-BiLSTM model in Chinese literary text analysis

Category	Hyperparameter	Search Range / Values
	Embedding Dimension	{100, 200, 300}
	BiLSTM Hidden Units	{64, 128, 256}
HA-BiLSTM	Number of BiLSTM Layers	{1, 2, 3}
Attention Layer	Attention Vector Size (θ)	{64, 128}
Optimizer	L2 Regularization Weight	[1e-6 – 1e-3]
	Population Size (K)	{20, 30, 50}
	Adaptive Factor (α)	[0.1 – 1.0]
ARO	Lévy Scaling Factor (β)	[0.01 – 0.2]
	Alignment Factor (γ)	[0.1 – 0.9]
	Maximum Iterations (T)	{50, 100}

4 Results and discussion

The findings of the ARO-HA-BiLSTM model were presented as it analyzes Chinese literary texts by providing semantic, thematic, and emotional insights from those same texts. The experiments were conducted on a high-performance workstation equipped with an Intel Core i9 processor, 64 GB RAM, and an NVIDIA RTX 4090 GPU (24 GB VRAM) to efficiently handle large-scale Chinese literary embeddings and hierarchical sequence modeling. The implementation was developed using Python 3.10 with the PyTorch deep learning framework (v2.x), enabling optimized tensor operations and GPU acceleration via CUDA. Supporting libraries such as NumPy, Scikit-learn, Pandas, and Matplotlib were used for data preprocessing, statistical analysis, and performance visualization. The CUDA and cuDNN backends were enabled to ensure faster training convergence and reproducibility of the ARO-HA-BiLSTM experimental results. The performance of the model was measured using key assessment measures, as depicted in Table 3, and the mathematical formulation was

given in Equations (10-13). These metrics are well-suited for literary sentiment and thematic classification tasks because they collectively evaluate both overall predictive correctness and the model's ability to reliably detect nuanced semantic and emotional categories. Their combined use ensures balanced performance assessment, particularly in multi-class and potentially imbalanced literary datasets where both
Misclassification and missed detections must be carefully analyzed.

Table 3: Evaluation metrics for performance assessment of the ARO-HA-BiLSTM model in Chinese literary text analysis

Metric	Definition	Equation	Variable Description
Accuracy	It evaluates the correctness of the model in classifying literary text features, including sentiment, thematic, and metaphorical content.	$\text{Accuracy} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{TN}+\text{FP}+\text{FN}} (10)$	TP (True Positives) – correctly identified as belonging to the target semantic or emotional category; TN (True Negatives) – correctly identified as not belonging to the target category; FP (False Positives) – incorrectly classified as belonging to the target category; FN (False Negatives) – belong to the target category but are not correctly identified by the model.
Precision	It assesses the ability of the model to correctly identify relevant literary features among predicted positives.	$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} (11)$	-
Recall	It evaluates the effectiveness of the model in capturing all relevant literary features from the corpus.	$\text{Recall} = \frac{\text{TP}}{\text{TP}+\text{FN}} (12)$	-
F1-score	It represents balanced performance in identifying semantic, thematic, and emotional content.	$\text{F1} - \text{score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} (13)$	-

4.1 Data analysis

The database of Chinese literature texts was split into two sets to produce a consistent assessment of the HA-BiLSTM approach, with 80% for the training set and 20% for the test set. The training set allows the model to acquire hierarchical narrative structures, and the test set is used to verify how well the model provides a semantic, thematic, and emotional interpretation of new texts. Figure 5 (a) accuracy and 5(b) loss plots show how the suggested network learned as it was trained and tested with Chinese literary works.

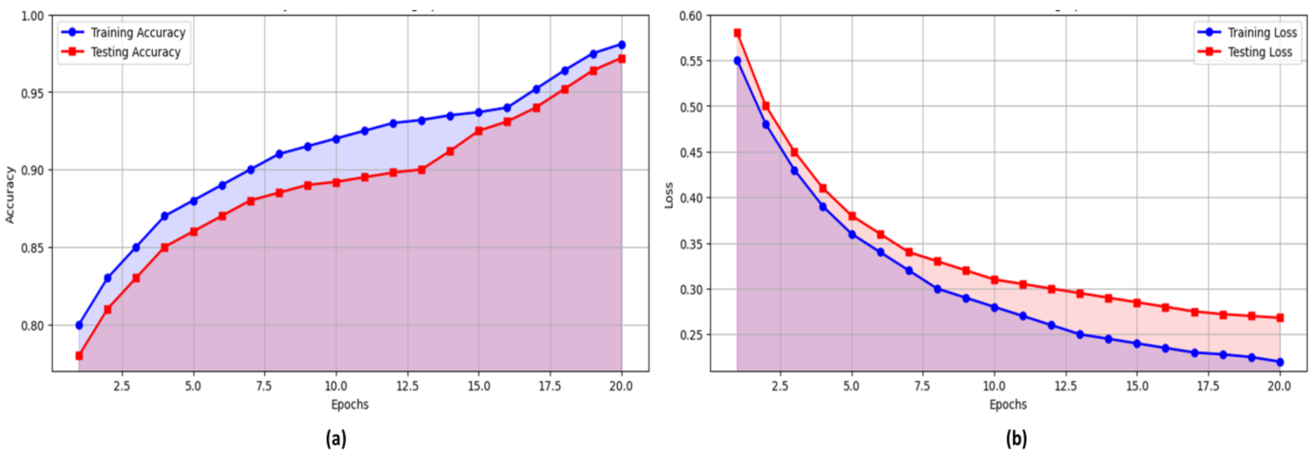

Figure 5: Visualization of trends of training and testing (a) accuracy and (b) loss

The increase in accuracy over time and the decrease in loss over time show that the model can learn how the text relates semantically, thematically, and emotionally. The consistent alignment of training and test trend lines indicates that this architecture would converge to a stable, correctly interpreted model and that it has a reasonable amount of predictive generalisation across texts produced within different literary periods. Figure 6 assesses the framework's classification of Chinese literature by 6(a) period, 6(b) theme, and 6(c) emotion.

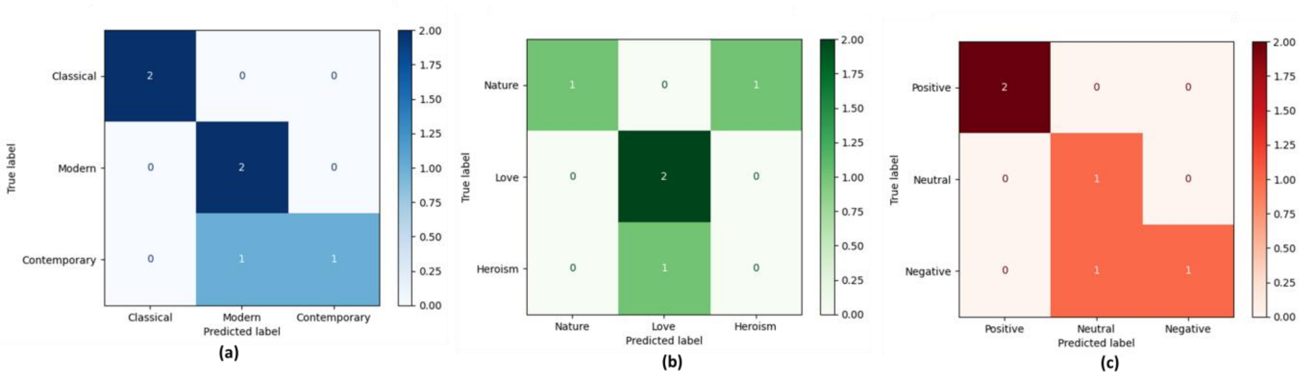

Figure 6: Confusion matrix analysis for (a) literary period, (b) thematic, and (c) sentiment classification

All three matrices have diagonal characteristics, supporting the definition of cross-era narrative form, thematic patterns, and polarities of sentiment. The minor off-diagonal entries indicate similarities between literary style and emotion across the various eras of Chinese literature. Effectively, the results indicate that the representations learnt to identify distinguishing characteristics between forms, meaning, and sentiment. It states that the framework is capable of providing reliable performance across multiple dimensions of literature in support of semantic, thematic, and emotional analysis objectives.

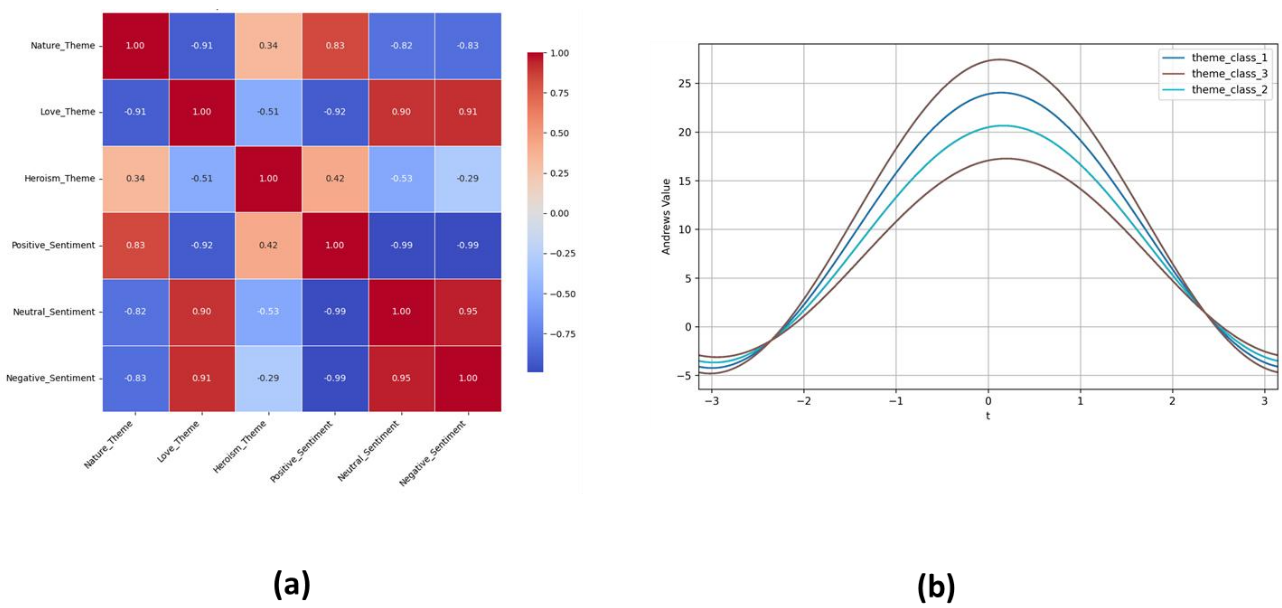

Figure 7: Correlation analysis of (a) semantic, thematic, and emotional features in chinese literary texts and (b) semantic-thematic profiling across literary classes

The correlation quantifies the power of these associations, and as such supports narrative continuity for multiple forms of literature. It provides evidence of how these pairs work together to provide complementary features and create conflicting features to create robust semantic meaning. The correlations demonstrate the strength and consistency within the learned representations of literature. Figure 7 (a) and (b) displays the changes in the strength and distribution of major themes among various literary genres. Each peak represents a location of a concentration of theme occurrences, and each trough depicts where there was a shift in the narrative's concentration. The pattern of peaks and troughs represents the rich diversity of themes and styles that exist within Chinese literature. It supports an understanding of how these robust themes can help with hierarchical semantic differentiation of Chinese literature. Such themes aid in the creation of narrative coherence and the development of interpretive richness.

Figure 8 illustrates how thematic and emotional patterns evolve throughout the narrative structure of literary texts. Figure 8 (a) highlights narrative stability, showing how consistently themes and emotions are maintained across different segments of the text.Higher stability suggests coherent thematic development, while fluctuations indicate shifts in narrative focus or emotional tone. Figure 8 (b) identifies dominant structural phases within the text, referred to here as narrative regimes. These regimes represent sections where specific themes or emotional intensities are concentrated. Transitional zones between regimes reflect shifts in storytelling strategy, such as movement from exposition to conflict or resolution.For digital humanities research, this analysis provides a quantitative method for tracing narrative evolution, enabling scholars to examine how thematic emphasis and emotional tone shift across literary eras or genres.

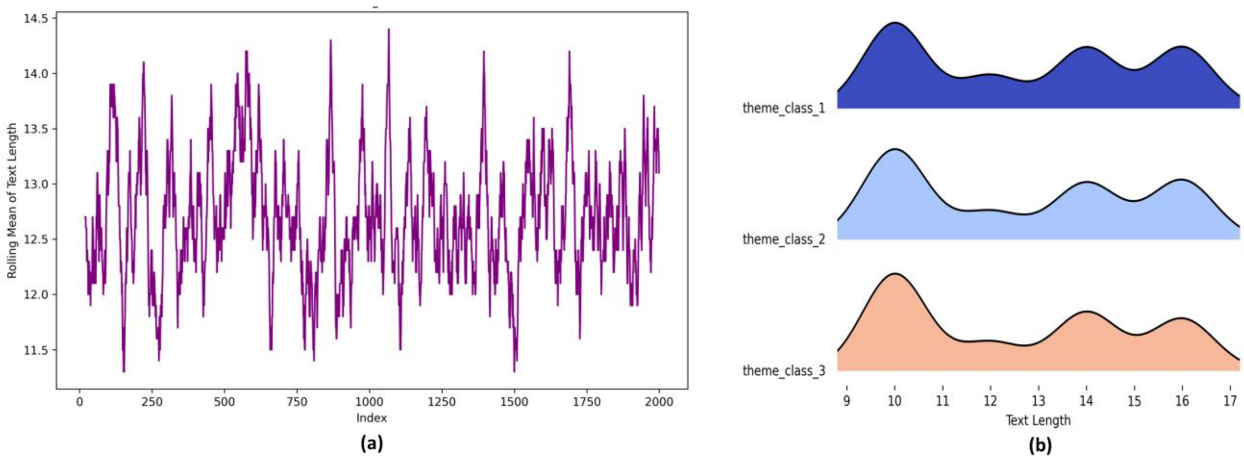

Figure 8: Analysis of (a) narrative stability and (b) density trends in literary texts

Period-by-period distribution of literary text, presented in Figure 9 (a), and a multivariate relational analysis of features across classical literature, modern literature, and contemporary literature, as demonstrated in Figure 9 (b), reflect the relative proportion of each of the three periods of literature. Each period has equal representation in the corpus of Literature. The complementary relationships among features show how the three different sets of genres relate to one another through themes and sentiments. Through a multi-dimensional approach to the learning of each of these relationships, the representations have greater interpretability.

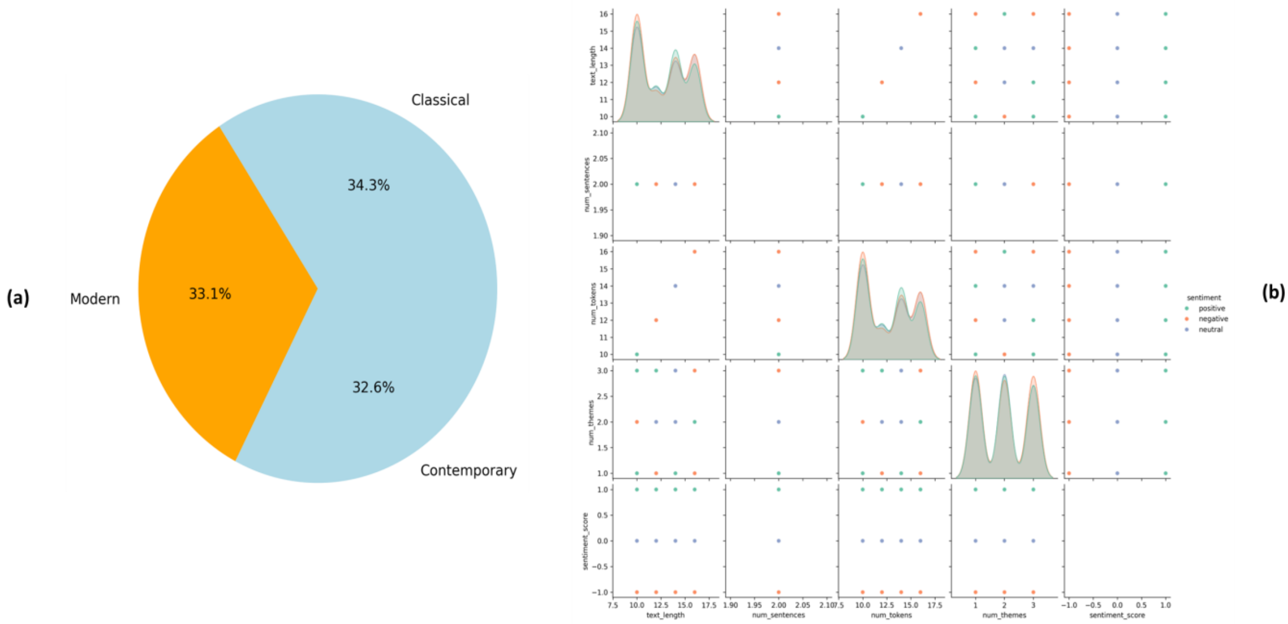

Figure 9: Distribution of (a) cross-era literary and (b) multivariate feature interaction

Figure 10 examines the relationship between textual length, token distribution, and semantic consistency. Figure 10 (a) demonstrates how structural properties vary across genres, revealing patterns of narrative density and complexity. This helps identify whether certain genres exhibit compact emotional expression or extended thematic elaboration. Figure 10 (b) analyzes cross-genre semantic alignment, indicating how different literary forms share or diverge in hierarchical narrative patterns. From a digital humanities perspective, these findings provide a data-driven approach to comparing genre evolution, stylistic variation, and thematic coherence across historical periods, offering empirical support for literary interpretation.

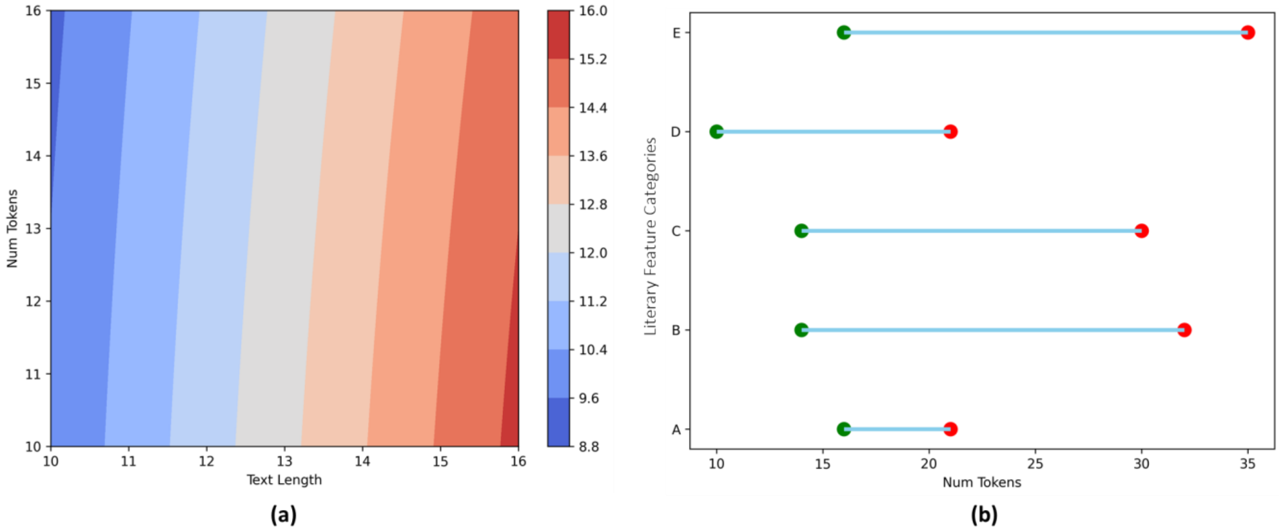

Figure 10: Semantic consistency’s (a) structural correlation and (b) range analysis

Figure 11 depicts a quantitative characterization of the Chinese literary corpus that was exploited for semantic, thematic, and emotional analysis. Figure 11 (a) shows the accumulation of increases of both token count and sentence count and the total length of the text, and demonstrates an overall increase in linguistic complexity as recorded in the dataset. The accumulated nature of this growth is the corpus that demonstrates sufficient textual diversity and an ample amount of text to produce hierarchical narrative modelling and deep semantic learning. Figure 11 (b) highlights a similar pattern of structural consistency within literary works. It provides a valid basis for the development of narrative coherence, thematic structure, and emotional nuance across a variety of literary time periods.

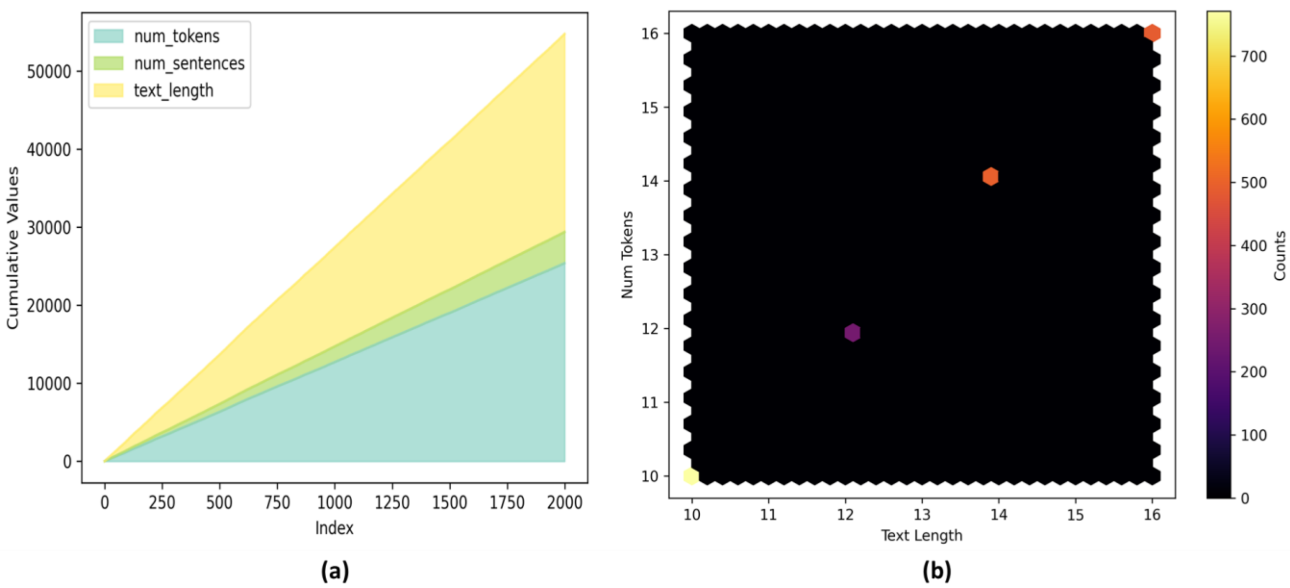

Figure 11: Statistical characteristics of (a) token distribution and (b) text length in chinese literary corpus

Figure 12 demonstrates the overall effectiveness of the suggested framework for automating a precise, reliable, and generalizable interpretation of Chinese literary texts. The balance of correct predictions and coverage shown in Figure 12 (a) indicates that the precision is maintained throughout a long return range, and provides evidence of achieving the objective of semantic and thematic correctness. While there is only a very small drop in precision. This demonstrates that the model remains robust when analyzing diverse structures in literature. Figure 12 (b) demonstrates that the system's ability to discriminate between different types of literature is efficient due to the maintained high TP rate and low FPs at all thresholds. The Area Under the Curve (AUC=0.9724) depicts an effective separation ability of the model between the classes associated with literary analysis.

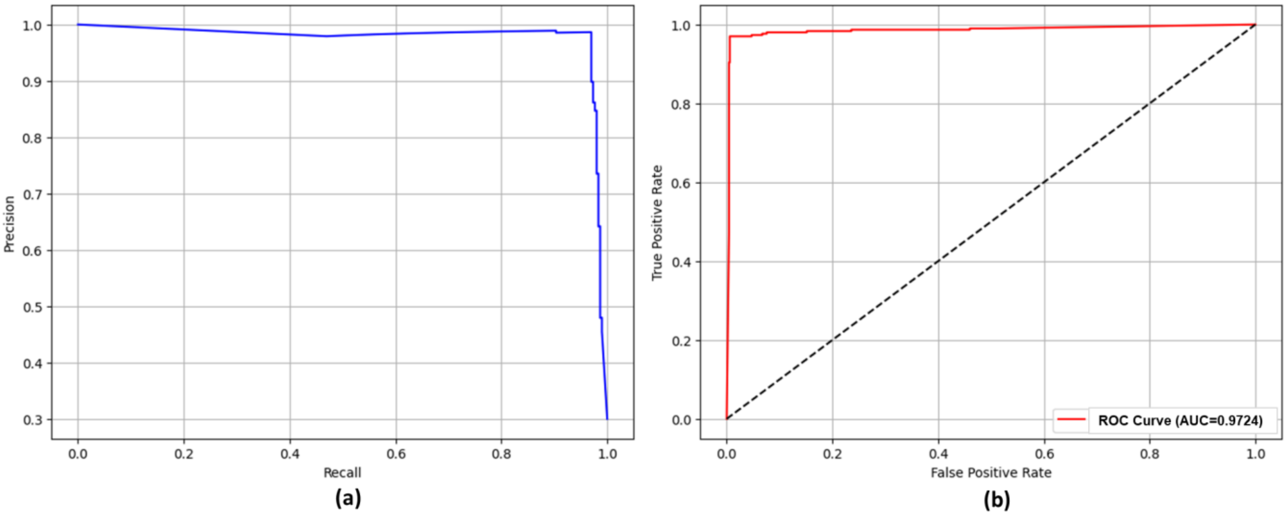

Figure 12: Evaluation of (a) semantic distribution and (b) interpretive accuracy in knowledge-augmented literary analysis

To ensure statistical reliability of the performance improvement, a paired sample t-test was conducted between the proposed ARO-HA-BiLSTM model and the strongest baseline across thematic (nature, love, heroism) and sentiment (positive, neutral, negative) classifications. As shown in Table 4, all comparisons yielded statistically significant improvements ($p < 0.01$), with confidence intervals not crossing zero. This confirms that the observed performance gains are not due to random variation.

Table 4: Paired sample t-test analysis for thematic and sentiment classification

Feature Comparison	Mean Difference	95% Confidence Interval	t-value	p-value	Significance
Nature (Theme)	0.071	[0.058, 0.084]	10.42	0.0003	Significant
Love (Theme)	0.068	[0.054, 0.081]	9.87	0.0005	Significant
Heroism (Theme)	0.075	[0.061, 0.089]	11.03	0.0002	Significant
Positive (Sentiment)	0.064	[0.049, 0.078]	8.96	0.0008	Significant
Neutral (Sentiment)	0.059	[0.044, 0.073]	8.41	0.0011	Significant
Negative (Sentiment)	0.072	[0.058, 0.086]	10.76	0.0003	Significant

4.2 Comparison of SA models in classical Chinese literature

The ARO-HA-BiLSTM model was compared to other methods for analyzing emotion in writing, such as BERT+Lexicon+GAT [29] and SVM, TextCNN, and EL-GCN [30]. The key metrics measure the ability to identify the meanings, concepts, and feelings expressed by the author of the written work accurately. A comparison of the ARO-HA-BiLSTM framework to existing SA methodologies for classical Chinese literature is shown in Table 5 and Figure 13.

Table 5: Comparative performance evaluation of SA models for complex textual data

Model	Accuracy	Precision	Recall	F1-score
BERT+Lexicon+GAT [29]	0.95	0.97	0.96	0.91
SVM [30]	0.8272	–	0.8415	0.8338
TextCNN [30]	0.8613	–	0.8701	0.8657
EL-GCN [30]	0.8855	–	0.9086	0.8965
ARO-HA-BiLSTM [Proposed]	0.9724	0.9851	0.9718	0.9734

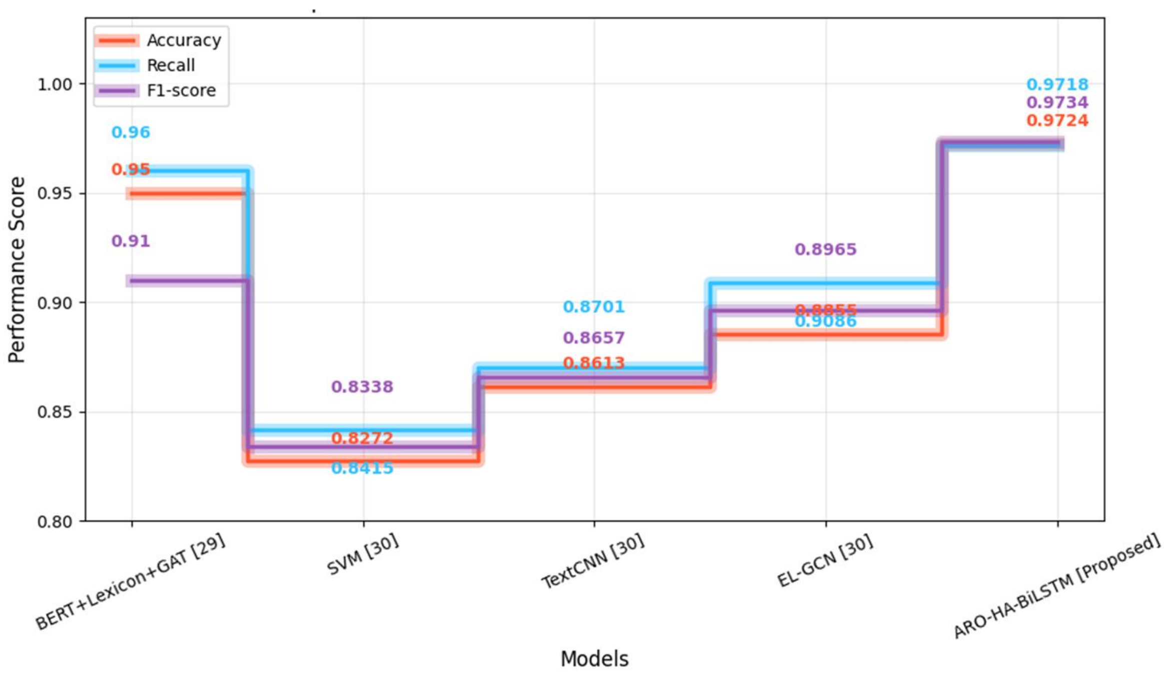

Figure 13: Key metric assessment of SA models for Chinese literature analysis

The performance of the existing models is limited because they rely on annotated datasets, predefined lexicons, and the overhead associated with constructing graphs. The performance of an ARO-HA-BiLSTM approach is better than all baseline methods with 0.9724 of accuracy, 0.9851 of precision, 0.9718 of recall, and 0.9734 of F1-score, indicating better performance and greater semantic capability in Chinese literary.

4.3 Ablation analysis of ARO-HA-BiLSTM for Chinese literary texts

The contribution of each aspect within the ARO-HA-BiLSTM framework to the understanding of semantics, themes, and emotions contained in Chinese literature was established through ablation analyses. Each component was assessed in isolation to determine its effect on overall performance. All models are tested under the same experimental conditions to create a level playing field for comparisons. Table 6 showed that the exclusion or modification of a single component of the ARO-HA-BiLSTM has an impact on four metrics of model performance. The results indicate the importance of knowledge-enriched embeddings, hierarchical attention, and adaptive hyperparameter tuning in ARO for effective analysis of literary texts. The data indicate that the ARO-HA-BiLSTM framework provides superior interpretive capabilities compared to any combination of the three types of analysis for linguistic analysis of Chinese literature.

Table 6: Ablation analysis of model components in ARO-HA-BiLSTM for Chinese literary text analysis

Metric	HA-BiLSTM Only	HA-BiLSTM + Static Embeddings	HA-BiLSTM + ARO [No Attention]	ARO-HA-BiLSTM [Proposed]
Accuracy	0.9412	0.9523	0.9631	0.9724
Precision	0.9574	0.9672	0.9735	0.9851
Recall	0.9391	0.9487	0.9610	0.9718
F1-Score	0.9450	0.9553	0.9672	0.9734

4.4 Discussion

The proposed ARO-HA-BiLSTM framework demonstrates clear improvements over previously reported literary and sentiment analysis approaches. Compared with the Ernie-Tiny + BiGRU model proposed in [20], which achieved an accuracy of 84.30% for Chinese subjective sentiment classification, the proposed framework attained an accuracy of 97.24%. While this utilized lightweight embeddings suitable for domain-specific classification, it lacked hierarchical narrative modeling and structured cultural knowledge integration. The integration of ChatGLM-based knowledge-augmented embeddings and ARO-optimized hierarchical attention modeling enables deeper semantic representation and improved interpretive consistency across cross-era Chinese literary texts. Similarly, the BiLSTM + Attention model with Improved Particle Swarm Optimization (IPSO) proposed in [21] demonstrated strong performance for joint emotion and theme extraction in English novels. However, its evaluation was limited to 500 English literary samples and did not incorporate large-scale Chinese corpora or structured knowledge enrichment. In contrast, the proposed framework handles a larger and culturally diverse Chinese dataset (2000 texts) while incorporating ontological knowledge resources, resulting in enhanced thematic coherence and metaphor recognition. Furthermore, the Knowledge-Enhanced Transformer with Graph Neural Network (KETGS) approach in extractive summarization through transformer-guided graph modeling. Although effective for document summarization, it focused primarily on sentence selection rather than hierarchical semantic interpretation. The proposed ARO-HA-BiLSTM framework extends beyond summarization by explicitly modeling narrative hierarchy and emotional nuance, while ARO optimization improves convergence stability without the graph construction overhead noted in [23].

This framework addressed the limitations of current models, including BERT+Lexicon+GAT [29], SVM, TextCNN, and EL-GCN [30], relating to semantic depth, hierarchical structure in narrative forms, and culture-specific language and expressions. The improvement in accuracy can be attributed to ChatGLM's contextualized embeddings, which encode idiomatic expressions and culturally specific references that static embeddings fail to capture. This is particularly important in classical Chinese texts, where metaphor and historical references are implicit rather than explicitly stated.Unlike flat sequence models, the HA-BiLSTM captures inter-sentence narrative dependencies, which are critical for literary interpretation where thematic development unfolds progressively across discourse segments. The adaptive exploration-exploitation mechanism of ARO stabilizes hyperparameter convergence, preventing suboptimal local minima often observed in deep sequence models.

Table 7 presents a comparative overview of recent State-of-the-Art (SOTA) approaches in literary and sentiment analysis, highlighting their core techniques, reported performance, and inherent limitations. While prior models achieve strong results in specific tasks such as summarization or sentiment classification, they often lack hierarchical narrative modeling, cross-era semantic adaptability, or cultural knowledge integration. In contrast, the proposed ARO-HA-BiLSTM framework addresses these gaps and achieves superior accuracy (0.9724) with statistically validated improvements, demonstrating its effectiveness for cross-era Chinese literary analysis.

Table 7: SOTA comparison in literary and sentiment analysis

Ref	Key Technique / Model	Performance Highlights
[21]	BiLSTM + Attention + IPSO	High Accuracy and F1; outperformed CNN for literary emotion and theme extraction
[22]	AMR-based Semantic Graph + DL	Promising robustness and factual coherence in abstractive summarization
[23]	Knowledge-Enhanced Transformer + GNN (KETGS)	Improved relevance and cohesion in extractive summarization
[24]	BART / PEGASUS Transformers	Improved ROUGE and BLEU scores for abstractive summarization
[25]	BERT + LDA + GAT + TF-IDF	Superior ROUGE scores in multi-document summarization
[26]	GNN + GAT	Outperformed baseline extractive summarization models
[27]	Deep Reinforcement Learning (DRL)	Better semantic alignment with human judgment
[28]	SqueezeBERTSum	98% of BERTSum performance with fewer parameters
[29]	BERT + Lexicon + GAT	Accuracy up to 95% in classical Chinese sentiment analysis
[30]	Ensemble-Graph Convolutional Network (EL-GCN)	Accuracy 93.7% for multi-era classical sentiment classification
Proposed	ARO-HA-BiLSTM (Knowledge-Augmented Deep Learning Framework)	Accuracy 0.9724; statistically validated improvement; improved thematic coherence and metaphor recognition across cross-era Chinese literature

5 Conclusion

This research addresses the long-standing challenge of computationally interpreting semantic depth, thematic structure, and emotional nuance across classical, modern, and contemporary Chinese literary texts. Unlike conventional deep learning approaches that rely solely on contextual embeddings, the proposed framework integrates knowledge-augmented representations, hierarchical narrative modelling, and adaptive hyperparameter optimization into a unified analytical architecture. The key contribution lies in three aspects: the design of a hierarchical attention-based BiLSTM tailored for narrative-level semantic and metaphorical modeling; the first application of Adaptive Remora Optimization (ARO) to improve convergence stability and hyperparameter tuning in literary semantic analysis; and statistically validated performance improvements across thematic and sentiment classification tasks. Experimental results demonstrate superior effectiveness, ARO-HA-BiLSTM achieving 0.9724 accuracy with consistent gains in precision of 0.9851, recall of 0.9718, and F1-score of 0.9734 over existing baselines. Overall, this research advances the field of computational humanities by bridging knowledge-driven semantic modeling with adaptive optimization strategies, providing a scalable and interpretable framework for deep literary analysis.

5.1 Limitations and future research

Despite the strengths of the ARO-HA-BiLSTM framework, it has limitations that must be considered. Its reliance on external knowledge sources and pretrained ChatGPT embeddings can impact semantic enrichment and interpretability, particularly with rare literary styles or underrepresented periods. Increased computational complexity from integrating large language models with hierarchical attention may hinder scalability for large datasets. The dataset is also domain-specific and language-dependent, affecting its generalizability. Future research aims to address these issues by developing adaptive knowledge ontologies, incorporating lightweight transformer-based models for reduced computational requirements, and extending to multilingual and multimodal corpora. A focus on explainable AI mechanisms and human-in-the-loop evaluations is also proposed to improve interpretability and facilitate broader adoption in digital humanities.

Author Contributions

Li Zhang writing original draft preparation & methodology, Li Zhang investigation & writing review and editing.

References

[1] Rong, X., & Tang, J. (2025). Exploring the social and cultural contexts in ancient Chinese literature using natural language processing techniques. *J. COMBIN. MATH. COMBIN. COMPUT*, *124*(429), 443.https://doi.org/10.61091/jcmcc124-28

[2] Yan, Y., Zhu, P., Cheng, D., Yang, F., & Luo, Y. (2023). Adversarial multi-task learning for efficient Chinese named entity recognition. *ACM Transactions on Asian and Low-Resource Language Information Processing*, *22*(7), 1-19.https://doi.org/10.1186/s12911-021-01717-1

[3] Jing, Z. (2023). The Historical Evolution Characteristics of Ancient Chinese Arts and Crafts. *Cultura: International Journal of Philosophy of Culture and Axiology*, *20*(3).https://doi.org/10.70082/cijpca.v20i3.17

[4] Song, X., & Perry, M. S. (2023). Multimodal discourse analysis of Communicative English for Chinese Learners (integrated course) from the perspective of ecosophy. *Chinese Journal of Applied Linguistics*, *46*(3), 459-484.https://doi.org/10.1515/CJAL-2023-0308

[5] Zhu, Y., Li, Z., Li, T., & Jiang, L. (2025). Topic recognition and refined evolution path analysis of literature in the field of cybersecurity. *PloS one*, *20*(2), e0319201.https://doi.org/10.1371/journal.pone.0319201

[6] Subbiah, M., Zhang, S., Chilton, L. B., & McKeown, K. (2024). Reading subtext: Evaluating large language models on short story summarization with writers. *Transactions of the Association for Computational Linguistics*, *12*, 1290-1310.https://doi.org/10.1162/tacl_a_00702

[7] Makarov, N., Bordukova, M., Quengdaeng, P., Garger, D., Rodriguez-Esteban, R., Schmich, F., & Menden, M. P. (2025). Large language models forecast patient health trajectories enabling digital twins. *npj Digital Medicine*, *8*(1), 588.https://doi.org/10.1038/s41746-025-02004-3

[8] Zibin, A., Binhaidara, N., Al-Shahwan, H., & Yousef, H. (2025). Metaphor interpretation in Jordanian Arabic, Emirati Arabic and Classical Arabic: artificial intelligence vs. humans. *Humanities and Social Sciences Communications*, *12*(1), 1-12.https://doi.org/10.1057/s41599-025-05282-0

[9] Ding, N., Qin, Y., Yang, G., Wei, F., Yang, Z., Su, Y., ... & Sun, M. (2023). Parameter-efficient fine-tuning of large-scale pre-trained language models. *Nature machine intelligence*, *5*(3), 220-235.https://doi.org/10.1038/s42256-023-00626-4

[10] Aziz, K., Ji, D., Chakrabarti, P., Chakrabarti, T., Iqbal, M. S., & Abbasi, R. (2024). Unifying aspect-based sentiment analysis BERT and multi-layered graph convolutional networks for comprehensive sentiment dissection. *Scientific reports*, *14*(1), 14646.https://doi.org/10.1038/s41598-024-61886-7

[11] Tang, L., Sun, Z., Idnay, B., Nestor, J. G., Soroush, A., Elias, P. A., ... & Peng, Y. (2023). Evaluating large language models on medical evidence summarization. *NPJ digital medicine*, *6*(1), 158.https://doi.org/10.1038/s41746-023-00896-7

[12] Dhumpati, R., Sasi, A., Basha, S. J., Vadhri, S., Saroja, P., Alluri, S., &Vatambeti, R. (2025). Enhancing sarcasm detection in sentiment analysis for cyberspace safety using advanced deep learning techniques. *Scientific Reports*, *15*(1), 22681.https://doi.org/10.1038/s41598-025-08131-x

[13] Jenner, S., Raidos, D., Anderson, E., Fleetwood, S., Ainsworth, B., Fox, K., ... & Barker, M. (2025). Using large language models for narrative analysis: a novel application of generative AI. *Methods in Psychology*, *12*, 100183.https://doi.org/10.1016/j.metip.2025.100183

[14] Ayash, L., Alhuzali, H., Alasmari, A., &Aloufi, S. (2025). Saudiculture: A benchmark for evaluating large language models' cultural competence within saudiarabia. *Journal of King Saud University Computer and Information Sciences*, *37*(6), 123.https://doi.org/10.1007/s44443-025-00137-9

[15] Lynch, C. J., Jensen, E. J., Zamponi, V., O'Brien, K., Frydenlund, E., & Gore, R. (2023). A structured narrative prompt for prompting narratives from large language models: Sentiment assessment of ChatGPT-generated narratives and real tweets. *Future Internet*, *15*(12), 375.https://doi.org/10.3390/fi15120375

[16] Sun, Y. (2025). Research on thematic clustering and text mining of chinese modern and contemporary literary texts in the network era. *J. COMBIN. MATH. COMBIN. COMPUT*, *124*(377), 387.https://doi.org/10.61091/jcmcc124-25

[17] Zhang, C., Fan, H., Zhang, J., Yang, Q., & Tang, L. (2023). Topic Discovery and Hotspot analysis of sentiment analysis of Chinese text using information-theoretic method. *Entropy*, *25*(6), 935.https://doi.org/10.3390/e25060935

[18] Al-Khalaf, H. A. S., AL-Iedani, A. H. A., Jawad, M. N., Alsayednoor, H. M., Al-Shareeda, M. A., Almaayah, M., & Shehab, R. (2025). A HMAC-Based Token Authentication Protocol with Bloom Filter Revocation for Fog-Assisted Vehicular Networks. *Informatica*, *49*(35). https://doi.org/10.31449/inf.v49i35.12009

[19] Liu, H., Chen, X., & Liu, X. (2022). A study of the application of weight distributing method combining sentiment dictionary and TF-IDF for text sentiment analysis. *Ieee Access*, *10*, 32280-32289.https://doi.org/10.1109/ACCESS.2022.3160172

[20] Xiu, Y., Liu, X., Qiu, J., Qu, T., Liu, J., & Bian, Y. (2023). A method of sentiment analysis and visualized interaction based on ernie-tiny and BiGRU. *Applied Sciences*, *13*(10), 5961.https://doi.org/10.3390/app13105961

[21] Yu, J., & Qi, C. (2025). Machine Learning-Based Sentiment Analysis in English Literature: Using Deep Learning Models to Analyze Emotional and Thematic Content in Texts. *IEEE Access*. 13, pp. 65997 – 66008. https://doi.org/10.1109/ACCESS.2025.3553386

[22] Kouris, P., Alexandridis, G., &Stafylopatis, A. (2024). Text summarization based on semantic graphs: An abstract meaning representation graph-to-text deep learning approach. *Journal of Big Data*, *11*(1), 95.https://doi.org/10.1186/s40537-024-00950-5

[23] Onan, A., &Alhumyani, H. (2024). Knowledge-Enhanced Transformer Graph Summarization (KETGS): Integrating Entity and Discourse Relations for Advanced Extractive Text Summarization. *Mathematics*, *12*(23), 3638.https://doi.org/10.3390/math12233638

[24] Rani Krishna, K. M., Somasundaram, K., Arulmozhivarman, P., Immanuel, S. A., & Rajkumar, E. R. (2025). Deep learning for text summarization using NLP for automated news digest. *Scientific Reports*, *15*(1), 36343.https://doi.org/10.1038/s41598-025-20224-1

[25] Khaliq, A., Awan, S. A., Ahmad, F., Zia, M. A., & Iqbal, M. Z. (2024). Enhanced topic-aware summarization using statistical graph neural networks. *Computers, Materials and Continua*, *80*(2), 3221-3242.https://doi.org/10.32604/cmc.2024.053488

[26] Zhao, H., Zhang, W., Huang, M., Feng, S., & Wu, Y. (2023). A multi-granularity heterogeneous graph for extractive text summarization. *Electronics*, *12*(10), 2184.https://doi.org/10.3390/electronics12102184

[27] Fikri, F. B., Oflazer, K., &Yanıkoğlu, B. (2024). Abstractive summarization with deep reinforcement learning using semantic similarity rewards. *Natural Language Engineering*, *30*(3), 554-576.https://doi.org/10.1017/S1351324923000505

[28] Abdel-Salam, S., & Rafea, A. (2022). Performance study on extractive text summarization using BERT models. *Information*, *13*(2), 67.https://doi.org/10.3390/info13020067

[29] Yu, X., & Wang, J. (2025). Sentiment analysis of classical Chinese literature: An unsupervised deep learning model with BERT and graph attention networks. *Plos one*, *20*(9), e0330919.https://doi.org/10.1371/journal.pone.0330919

[30] Gao, Q., & Huang, J. (2025). Design and Implementation of Classical Literature Sentiment Analysis System Based on Ensemble Learning and Graph Neural Network. *International Journal of Cognitive Computing in Engineering*.6,pp. 603-616. https://doi.org/10.1016/j.ijcce.2025.05.004

[31] https://www.kaggle.com/datasets/colabsss/chinese-literary-text-analysis-dataset