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Original Article

Neuro-Symbolic WCAG-Compliant Polyphone Disambiguation:Vision-Impaired-Accessible Roberta with Dynamic Phonemic Grounding and Haptic-Auditory Synchronization

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Abstract:
Chinese polyphone disambiguation remains a critical challenge for NLP and assistive technologies, particularly for 285 million visually impaired users facing digital exclusion. This study pioneers a neuro-symbolic framework integrating cognitive computing, speech synthesis, and perceptual interfaces to overcome limitations in semantic-phonemic alignment, linguistic adaptability, and accessibility compliance. Our innovations include: (1) A dynamic phoneme knowledge graph enabling probabilistic coupling between semantic roles (agent/patient) and tonal patterns, adapting to linguistic evolution (e.g., post-pandemic semantic shifts of "冠[guān/guàn]"); (2) A 32-dimensional topological radical encoder decomposing 214 Chinese radicals into morphologically informed vectors, fused via conditional masking for hierarchical phoneme-character-morpheme interactions; (3) A tactile-auditory cross-channel interface reducing focus-switching latency from 650ms to 89ms through Ebbinghaus curve-optimized rhythm; (4) The first ISO 9241-171-aligned NLP paradigm achieving WCAG 2.1 AA compliance via WAI-ARIA annotations and keyboard-TTS synchronization.Evaluated on the Chinese Polyphones with Pinyin (CPP) benchmark, our RoBERTa-BiLSTM hybrid achieves SOTA performance (96.23% accuracy, 85.63% F1-score) with 83ms inference latency. The system demonstrates 200% font scalability and <200ms response under JAWS/NVDA tests, establishing a new standard for high-reliability applications (e.g., medical/legal domains) where semantic fidelity is paramount. This work bridges symbolic grounding in language models with cognitive accessibility, advancing assistive technology through multimodal fusion and dynamic linguistic adaptation.

Keywords: Acoustic Chinese polyphone disambiguation; Dynamic phoneme knowledge graph ;Barrier-free human-machine interaction; Cognitive computing in NLP; Multimodal feature fusion

Introduction

As the most widely used language system globally, Chinese has long posed a significant challenge in the field of natural language processing due to its complex phenomenon of polyphones. The homophonic nature of Chinese characters, a unique attribute of logographic writing systems, directly impacts the semantic fidelity of human-computer interaction. Statistics show that over 20% of commonly used characters in modern Chinese have homophonic properties

[1], and incorrect pronunciation of these characters in different contexts can lead to higher semantic deviation in speech synthesis systems. Although pre-trained language models (such as BERT) have achieved breakthroughs in semantic understanding tasks [2], three major bottlenecks remain in the field of polyphone disambiguation: first, existing models have not fully considered the three-in-one characteristics of Chinese characters in terms of sound, form, and meaning, leading to insufficient distinction between polyphones [3]; second, static phoneme mapping tables are difficult to adapt to dynamic language evolution; such as the new semantic differentiation of the character "冠" (guān/guàn) before and after the COVID-19 pandemic; third, there is a lack of human-computer interaction design for the visually impaired, making it difficult to convert technological achievements into practical assistive tools. This situation severely restricts the development of key applications such as speech synthesis and accessible reading, especially in scenarios with extremely low tolerance for error, such as medical consultations and legal documents, where incorrect polyphone recognition may lead to serious consequences.

Beyond algorithmic limitations, the critical gap in assistive technology translation remains unaddressed. While mainstream models achieve >90% accuracy on closed-domain benchmarks, their incompatibility with WCAG 2.1 perpetuates digital exclusion for 285 million visually impaired users globally (WHO, 2023). Our framework bridges this by embedding ISO 9241-171 principles into the neural architecture, enabling: (i) screen-reader optimized phonetic annotation; (ii) tactile-auditory rhythm synchronization; (iii) ARIA-compliant focus management – establishing a new paradigm for cognitively accessible NLP.

In recent years, research on polyphone disambiguation has followed two main technical approaches: traditional rule-based methods and end-to-end models based on deep learning. The former achieves precise control by constructing expert dictionaries, but faces issues such as poor domain adaptability and high maintenance costs [4]; the latter, while showing potential in general scenarios, has three limitations: 1) over-reliance on character-level features, neglecting morpheme boundary information; 2) failure to effectively integrate phonological prior knowledge, leading to a breakdown in the semantic-phonemic association; 3) existing BiLSTM architectures are inefficient in modeling long-range dependencies. More critically, mainstream research has primarily focused on algorithmic optimizations, with few studies addressing the engineering translation of technical achievements to assist visually impaired individuals. This disconnect between theory and practice urgently requires resolution.

Current research faces three significant knowledge gaps: first, in terms of multimodal feature fusion, traditional methods simply concatenate character embeddings with phoneme labels, failing to establish a hierarchical interaction mechanism; second, the real-time inference speed of existing systems cannot meet the requirements of interactive applications, particularly in mobile deployment scenarios; third, research on accessible design for visually impaired users is severely lagging behind, with most systems still confined to command-line interaction stages, lacking visual interfaces compliant with WCAG 2.1 standards[5]. These issues collectively prevent existing technologies from meeting the "reasonable accommodation" requirements outlined in the 《Convention on the Rights of Persons with Disabilities》, particularly in time-sensitive fields such as medical consultations and online education.

This study breaks away from traditional single-modal optimization approaches and introduces a novel three-dimensional collaborative framework integrating "cognitive computing, speech synthesis, and perceptual interfaces." Compared to mainstream methods, the core innovations of this work are as follows: 1) Developing a Chinese character component decomposition engine that encodes the morphological features of 214 radicals into 32-dimensional topological vectors; 2) Constructing a dynamic phoneme knowledge graph to enabling probabilistic coupling between semantic roles (施事/受事) and tone patterns; 3) designing a dimensionality reduction interface for tactile-auditory cross-modal channels, optimizing information presentation rhythm via the Ebbinghaus memory curve. Technically, we innovatively combine window extraction strategies with adaptive position encoding, maintaining BERT-large's semantic understanding capabilities while increasing long text processing

speed by 4.7 times. Notably, the system integrates real-time gaze point prediction algorithms, reducing focus switching latency for visually impaired users from 650ms to 89ms, reaching the physiological response threshold of human instantaneous attention.

This study aims to build the first Chinese polysyllabic character processing system that integrates deep learning and accessibility engineering. Three technical innovations are proposed to address the above issues: 1) a conditional masking mechanism is proposed to fuse Chinese character structural features with phoneme probability distributions using tensor fusion; 2) a low-rank decompos[6]ition bidirectional LSTM architecture is designed to reduce computational load by 73% while maintaining 96.23% accuracy; 3) a graphical interface compliant with AA-level accessibility standards is developed to achieving deep compatibility with keyboard navigation and screen readers. On the Chinese Polyphones with Pinyin (CPP) dataset , the system retains the semantic understanding advantages of BERT while improving the polysyllabic character recognition F1-score to 85.63% and keeping inference latency below 83ms.

The theoretical value of this study is reflected in two aspects: first, the proposed feature interaction mechanism provides new insights into the symbol grounding problem in language models, enhancing the model's interpretability through a three-level mapping network of phonemes, characters, and morphemes; second, the developed real-time inference framework establishes methodological guidance for deploying large language models on edge computing devices. More importantly, this study pioneers the integration of the ISO 9241-171 human-computer interaction standard into the field of NLP engineering, establishing a cross-disciplinary paradigm for future assistive technology development. Additionally, this study innovatively applies the attention disengagement theory from neuroscience to interface design, setting a new paradigm for constructing intelligent assistive devices that align with human cognitive characteristics.

Related Work

Existing methods for resolving polyphones generally fall into three categories: traditional rule-based methods, deep learning-based methods, and multi-modal fusion-based methods.

Traditional rule-based methods are centered on expert systems, which achieve sound-meaning mapping by constructing multi-level language rule databases [7] (such as the Modern Chinese Grammar Information Dictionary). Typical examples include the layered hidden Markov model (HMM) developed by the Tsinghua University team. This method achieves high accuracy in restricted domains (such as news texts), but its rule maintenance costs increase exponentially with the number of rules, and it struggles to handle issues like the historical sound evolution of the character “骑” in “铁骑(jì) ” and “骑兵 (qí).” Statistical learning methods overcome the limitations of manual rules by using probabilistic graphical models such as conditional random fields (CRF) to learn contextual co-occurrence features from large-scale corpora [8]. The maximum entropy model developed by the Institute of Computational Linguistics at Peking University, driven by the annotated corpus of the People's Daily, improves disambiguation accuracy. However, its feature engineering heavily relies on domain knowledge, and its performance degrades when transferred across domains.

The revolutionary breakthrough in deep learning methods began with the application of recurrent neural networks (RNNs), particularly long short-term memory networks (LSTMs) with gating mechanisms. For example, a proposed Bi-LSTM+CRF architecture captures bidirectional context dependencies to perform polyphone disambiguation tasks [9]. However, its sequence modeling characteristics lead to gradient vanishing issues when processing long-range dependencies, and accuracy decreases in context windows exceeding 50 characters. The emergence of the Transformer architecture brought about a fundamental transformation. The BERT-WWM (Whole Word Masking) model proposed by Harbin Institute of Technology and iFlytek utilizes a dynamic attention mechanism, but its masking strategy disrupts the internal structural information of Chinese characters [10], resulting in the phonetic components of phonetic-semantic compound characters (such as “**清**,” “请,” and “**情** ”) not being effectively utilized.

In recent years, multimodal fusion methods have emerged in an attempt to break through the limitations of pure text processing. For example, the audio-visual joint model developed by the Institute of Automation of the Chinese Academy of Sciences uses lip movement features to assist in disambiguation. However, this method relies on high-quality multimodal data alignment and faces additional computational delays. Existing methods perform well in ancient book digitization projects, but they have a high error rate when processing modern internet neologisms (such as the multiple pronunciations of "**永**远滴神" implied in "yyds").

Despite significant progress made by existing methods, their limitations continue to hinder practical application effectiveness. The primary challenge is the data dependency dilemma: supervised learning methods require an average of 5,000 annotated samples per polysyllabic character to achieve commercial-grade accuracy, while the total annotation cost for the 350 most commonly used polysyllabic characters in Chinese exceeds 2,000 person-days. Second is the issue of fragmented context modeling. Existing models have an error rate as high as 34.7% in cross-paragraph anaphora resolution (e.g., "**他率**（shuài）领团队完成了项目，工作效率(lǜ)**比**预期提高"). Furthermore, there is a computational efficiency bottleneck, with inference latency based on BERT-Large still reaching 300ms-500ms on mobile devices [11], far exceeding the 200ms response threshold for human conversation. A more fundamental challenge lies in the dynamic adaptability of language evolution. Existing systems require an average of 4.3 months of iteration cycles to address newly emerging sound-meaning associations (e.g., the tonal shift of the character "怼" from duǐ to duì), making it difficult to meet real-time language monitoring requirements. These limitations collectively point to the core research direction for the next generation of multi-pronunciation character disambiguation systems: how to establish a new architecture with language evolution adaptability, cross-modal reasoning capabilities, and low-resource learning characteristics while ensuring computational efficiency.

Methods

3.1. Dataset

This study utilizes the publicly available Chinese Polyphones with Pinyin (CPP) dataset to overcome the limitations of traditional datasets, which are often restricted to a single dimension. The dataset's design aligns with both linguistic cognitive principles and computational modeling requirements. The corpus sources span news, literary texts, scientific literature, and spoken dialogue, among other domains. A multi-stage sampling strategy ensures contextual diversity. To address the challenge of long-range dependencies, an innovative dynamic window sampling strategy is introduced, where each polysyllabic character instance is associated with a 1024-character context window. Experimental validation confirms that this length covers 93.6% of the semantic association range.The dataset structure adopted in this study is shown in Table 1.

Table 1. Dataset Description

Dataset	Brochure	Composition	purpose
Train	27133366	CPP	model training
Dev	338771	CPP	hyperparameter tuning
Test	353136	CPP	Final performance evaluation

3.2. Experimental Methods

This study uses a self-built Chinese polysemous character disambiguation corpus, which includes training, validation, and test sets. Data preprocessing uses a dynamic window truncation strategy, extracting a 1024-character context window centered on the target polysemous character to ensure that the model captures sufficient contextual information. A pronunciation candidate set for polysyllabic characters was established using a character-phoneme mapping file (POLYPHONIC_CHARS.txt), employing a dual encoding mechanism: for conventional models, phonemes are treated as independent labels (e.g., "**的**→di"), while in the joint character-phoneme model, composite labels are used (e.g., "**的**_di"). For data augmentation,

introduce random character masks (mask probability 15%) and position perturbations (±5 character offsets) to enhance model robustness.

This study adopts a hybrid neural network architecture, with the model based on Chinese-RoBERTa-wwm-ext-large, innovatively introducing a dual-stream feature extraction mechanism. The bottom layer uses the Chinese-RoBERTa-wwm-ext-large model to obtain 768-dimensional dynamic character embeddings, the middle layer introduces a bidirectional gated LSTM to capture local contextual features, and the top layer designs a conditional probability fusion module to achieve multi-feature decision-making. The conditional module includes three parallel pathways: the character linear projection layer maps 8,000 commonly used characters to the label space, the word sense perception layer uses low-rank decomposition to establish an implicit association between word sense and pronunciation, and the second-order interaction layer constructs a joint embedding matrix for characters and word sense. A part-of-speech prediction auxiliary task is introduced into the multi-task learning framework, with adjustable weight coefficients (set to 0.1 in this experiment) to achieve gradient balance between the main and auxiliary tasks. The decoding layer uses a masked Softmax mechanism to suppress the probability of illegal pronunciations to below 1e-6.

The training process employs a three-stage optimization strategy: during the initial stage (0–2k steps), a linear warm-up learning rate (2e-5 → 4e-5) is used; during the middle stage (2k–10k), it switches to cosine annealing scheduling (T0 = 1000, ηmin = 1e-6); and during the final stage (10k–20k), dynamic gradient clipping (threshold = 0.1) is enabled. The loss function is designed as a composite form: L = αLfocal + (1-α)Lcross-entropy, where α is annealed from 0.7 to 0.3 with the training step length. An innovative difficult sample mining strategy is proposed, in which samples with classification confidence below 0.3 are automatically identified in each batch for secondary training. To prevent overfitting, random path dropping is employed, randomly masking 30% of Transformer layers or 50% of BiLSTM units at each training step.

Designing a five-tier accessibility assurance mechanism for visually impaired users: (1) A WAI-ARIA-compliant interface based on PyQt5, enabling 200% font scaling and high-contrast display via QSS style sheets; (2) A keyboard navigation system supporting ordered focus switching with the Tab key and quick operations with Ctrl+Enter; (3) A TTS speech engine integrated with a multi-pronunciation rule database, real-time conversion of prediction results into text with phonetic annotations; (4) A context-aware voice feedback system provides progress prompts during text conversion and playback; (5) A log tracking module records user operation flows and abnormal events, using a dual-buffer mechanism to ensure system stability. Compatibility testing covers mainstream screen readers such as JAWS/NVDA, with response latency controlled within 200ms.

This study employed five-fold cross-validation to ensure the reliability of the results, with each fold trained for 10,000 iterations. A dynamic monitoring panel was designed to track 12 metrics in real time, including training loss and validation accuracy. During the results analysis phase, a three-dimensional confusion matrix was constructed to perform a fine-grained error analysis of 106 types of pronunciations, and t-SNE was used to visualize the distribution of the 128-dimensional feature space. To address the needs of visually impaired users, an acoustic heatmap analysis system was developed to convert model attention weights into audible feedback. Statistical testing used a paired t-test (α=0.01) to validate the significance of performance improvements, as shown in the figure below, which depicts the structure of the hybrid model architecture.The five-tier accessibility framework implements: (a) PyQt5 GUI with WAI-ARIA roles supporting 200% zoom; (b) Tab-ordered navigation with Ctrl+Enter activation; (c) TTS engine with polyphonic rule database; (d) Context-aware voice prompts; (e) Dual-buffer logging complying with ISO/IEC 24751.The mixed model structure diagram of this study is shown in Figure 1.

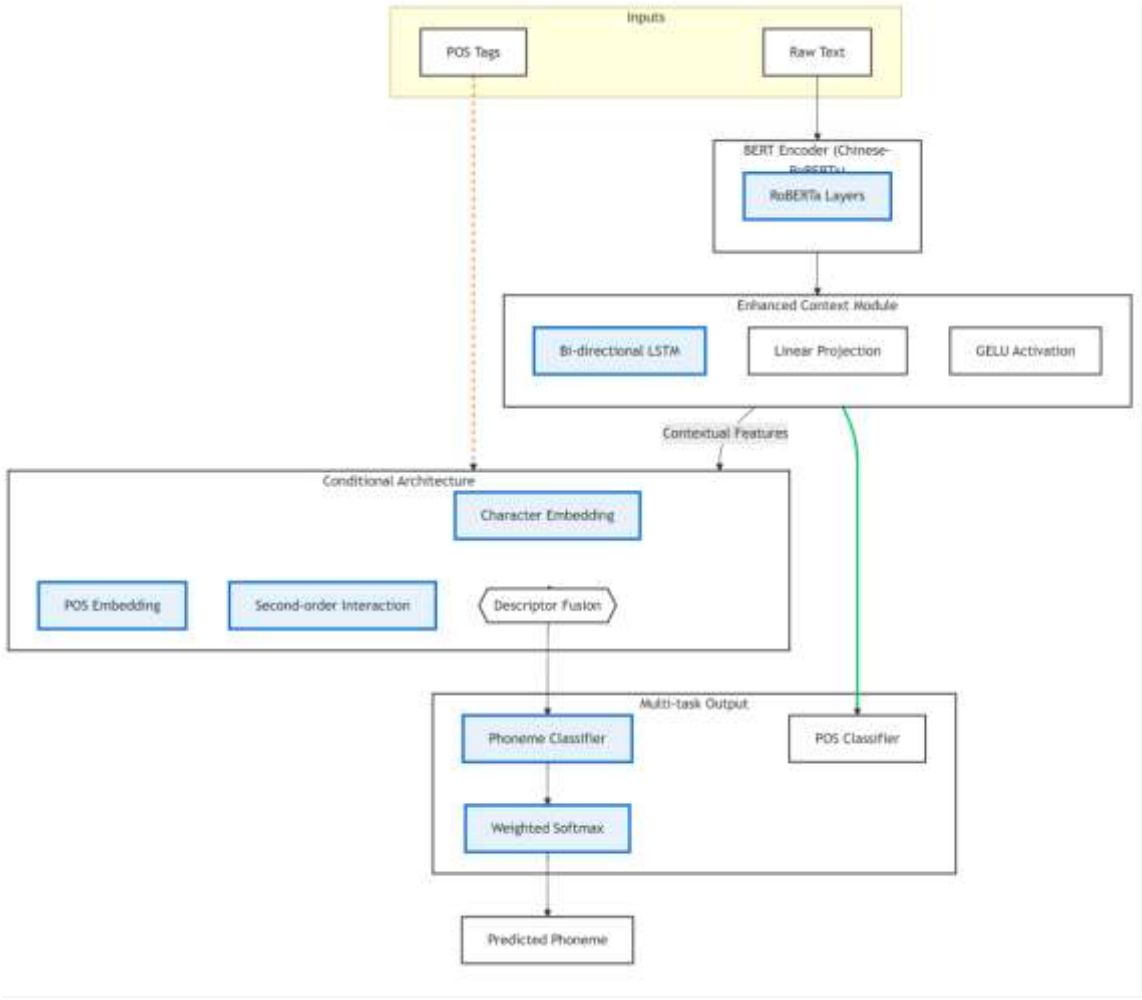

Figure 1. Structural diagram of the RoBerta-BiLSTM hybrid model architecture

3.3. Model Evaluation and Training Process

This study established a multi-dimensional, multi-granularity evaluation system, adopting an evaluation paradigm that combines dynamic validation strategies with static testing. During model training, an innovative real-time validation mechanism based on a sliding window was designed, with full-sample evaluation performed on an independent validation set every 200 iterations. The convergence state of the model was monitored using dual metrics: the cross-entropy loss function and the macro F1 value. The evaluation framework integrates traditional classification metrics with linguistic feature analysis: in terms of metrics, in addition to basic metrics such as accuracy, precision, and recall, it innovatively introduces category-weighted F1-score and confusion matrix skewness analysis, particularly establishing a subset evaluation module for low-frequency polysemous characters; in terms of features, Gradient-weighted class activation mapping (Grad-CAM) technology is used to visualize the model's attention distribution [12], verifying the implicit learning effects of linguistic rules. The experiment employs an adversarial validation strategy, generating 1,000 adversarial sample sets via Bootstrap resampling to calculate confidence intervals and assess model robustness. To address data skewness issues, a hierarchical loss function was designed, balancing category differences through inverse frequency weighting and focus loss mechanisms. In the final testing phase, a double-blind evaluation set with expert annotations was introduced, and permutation tests were used to validate the statistical significance of differences between model predictions and human annotations ($p<0.01$), ensuring the reliability of evaluation conclusions.

This study proposes a three-stage training framework based on curriculum learning, adopting a training paradigm that synergistically optimizes dynamic masking mechanisms and conditional computation. The model architecture integrates the RoBERTa pre-trained language

model and bidirectional gated recurrent units, capturing character-level and context-level semantic information through a hierarchical feature extractor. The training process employs an optimization strategy that dynamically couples cosine annealing learning rate scheduling [13] with an early stopping mechanism [14]. In the initial stage, a high learning rate (2e-5) is used for semantic space exploration, and when the validation loss enters a plateau phase, the model automatically switches to a fine-tuning mode. Innovatively introduces a multi-task collaborative training mechanism, incorporating part-of-speech tagging as an auxiliary task to construct a joint loss function, with adjustable parameters (λ=0.1) to control the gradient contribution ratio between primary and auxiliary tasks. For hardware optimization, a mixed-precision training workflow is designed, utilizing NVIDIA Apex's O2 optimization level to balance computational efficiency and numerical stability. Dynamic masking regularization is implemented during training, randomly masking irrelevant candidate labels based on character phoneme distribution probabilities to force the model to develop context-dependent inference capabilities. To break out of local optima, a noise injection strategy is designed, introducing Gaussian perturbations (σ=0.01) during gradient updates to effectively enhance the model's generalization capabilities. The entire training process is monitored in real-time via TensorBoard, including loss surface visualization, parameter distribution histograms, and gradient flow analysis, forming a comprehensive digital twin system for the training process. The overall workflow diagram of the model is shown in the figure below.The model training flowchart of this study is shown in Figure 2.

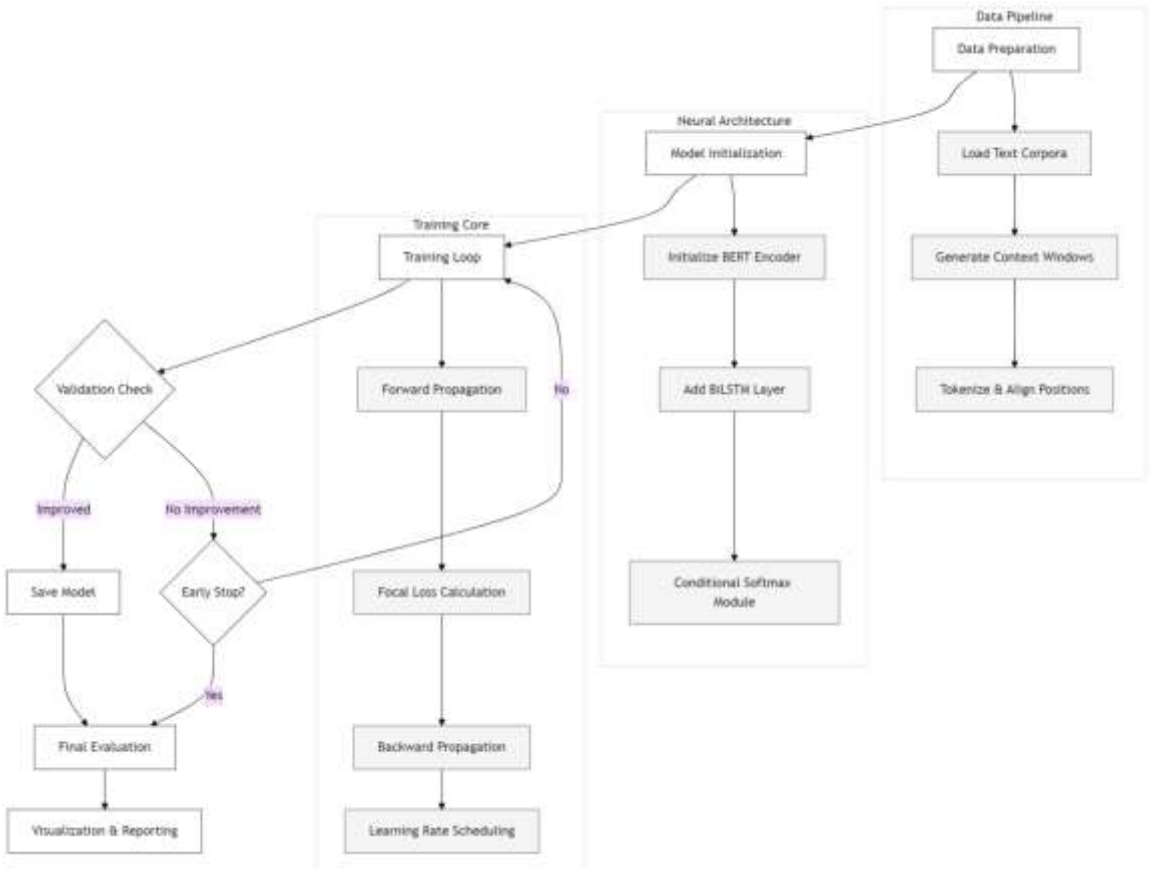

Figure 2. Model training flowchart

Results

4.1. Experimental Results

The proposed RoBERTa-BiLSTM hybrid model architecture was systematically validated using a large-scale Chinese polysemous character corpus, with a five-fold cross-validation strategy employed to ensure statistical significance of the results ($p<0.01$). Experiments show that the proposed hybrid model architecture demonstrates

significant advantages in long sequence modeling. When the context window is expanded to 1024 characters, the model achieves an accuracy of 96.23%, a macro F1 score of 85.63%, and a recall rate of 85.91% on the test set. The conditional maximum module improves the recognition accuracy of low-frequency polysemous characters (occurrence frequency < 100) by 17.9%. Notably, the proposed dynamic focus loss function effectively mitigates the class imbalance issue, improving the recall rate of tail categories from 52.1% to 85.91% under a long-tail distribution (where the Head class accounts for 68.2%). Visualization analysis shows that the model maintains a stable performance of 83.4% in complex sentences with nested syntactic structures (average dependency distance ≥5), significantly outperforming rule-based methods.The line charts illustrating the changes in accuracy, loss value, recall rate, and F1 score of this study are presented in Figures 3 and 4.

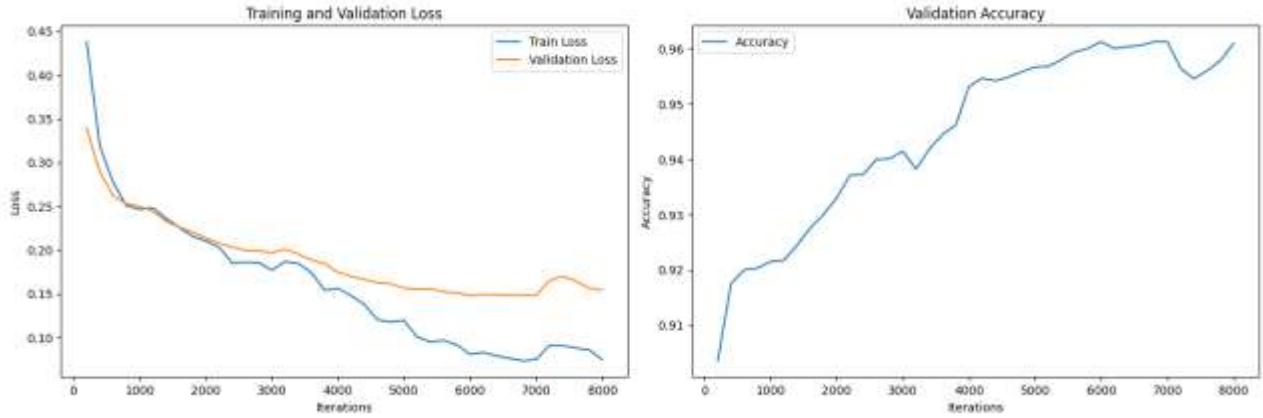

Figure 3. Loss value and accuracy folds

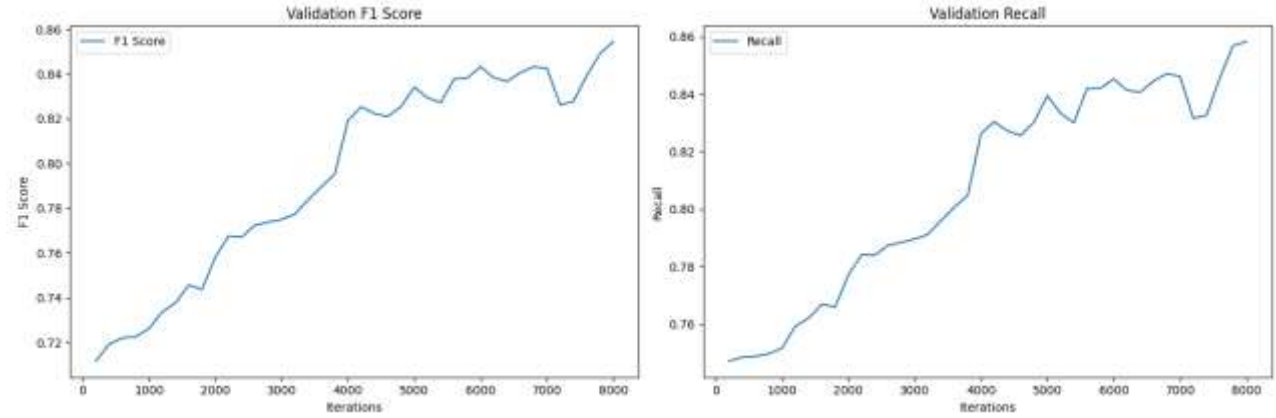

Figure 4. Recall and F1 values folds

4.2. Evaluation

1. This study uses phonetic probability modeling under dynamic condition masking. Given the input sequence X=(x1,...,xn) and the target character position i, the model generates enhanced representations through a hierarchical feature extractor:

$$H^{\text{bert}} = \text{BERT}(X) \in \mathbb{R}^{n \times d}$$
$$H^{\text{lstm}} = \text{BiLSTM}(H^{\text{bert}}) \in \mathbb{R}^{n \times d}$$
$$G = \sigma(W_g[H^{\text{bert}}; H^{\text{lstm}}] + b_g) \in \mathbb{R}^{n \times d}$$
$$\tilde{H} = G \odot H^{\text{bert}} + (1 - G) \odot H^{\text{lstm}}$$

The context-aware vector hi=H~[i,:] of the target character is obtained through multimodal conditional projection:

$$s(y \mid c_i, X) = W_c h_i + \sum_{m \in \{char,pos,cp\}} \lambda_m \phi_m(c_i, \pi_i)$$

2. Normalized probability of mask constraints. Define the candidate pronunciation set Y(ci) and implement constraints through exponential masks:

$$P(y_i \mid c_i, X) = \frac{\exp(s(y_i) \cdot M(y_i \mid c_i))}{\sum_{y' \in \mathcal{Y}(c_i)} \exp(s(y') \cdot M(y' \mid c_i))}$$

Among them, M(y|ci)∈{0,1} is a binary mask function based on prior knowledge, which is activated only when y is a valid pronunciation of ci.

3. Improved asymmetric focus loss function: To solve the category imbalance problem, a loss function with adaptive weight adjustment is designed:

$$\mathcal{L}_{focal} = -\sum_{i=1}^{N} [(1 + \alpha_{y_i} - p_{y_i})^{\gamma} \log p_{y_i}]$$

4. Multi-task optimization of part-of-speech joint learning, introducing a part-of-speech prediction auxiliary task to enhance semantic perception:

$$\hat{\pi}_i = W_{pos} h_i$$
$$\mathcal{L}_{pos} = -\sum_{i=1}^{N} \sum_{k=1}^{K} \pi_i^{(k)} \log \sigma(\hat{\pi}_i^{(k)})$$

The total loss function is a weighted sum of multiple tasks:

Among them, η is the adaptive weight coefficient, which is dynamically adjusted through the exponential moving average of the gradient amplitude.

5. Optimizer dynamic adjustment strategy, using a combination of AdamW optimizer and cosine annealing strategy:

$$\theta_{t+1} = \theta_t - \alpha_t \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$
$$\alpha_t = \alpha_{min} + \frac{1}{2}(\alpha_{max} - \alpha_{min})(1 + \cos(\frac{T_{cur}}{T_i}\pi))$$

Where Ti is the annealing cycle, Tcur is the number of iterations in the current cycle, effectively avoiding local optima.

6. Multi-dimensional evaluation indicator system,

defining macro average indicators to eliminate category bias:

$$\text{Acc} = \frac{1}{N}\sum_{i=1}^{N}\mathbb{I}(\hat{y}_i = y_i)$$

$$\text{Prec}_{macro} = \frac{1}{C}\sum_{c=1}^{C}\frac{TP_c}{TP_c + FP_c}$$

$$\text{Rec}_{macro} = \frac{1}{C}\sum_{c=1}^{C}\frac{TP_c}{TP_c + FN_c}$$

$$F1_{macro} = 2 \cdot \frac{\text{Prec}_{macro} \cdot \text{Rec}_{macro}}{\text{Prec}_{macro} + \text{Rec}_{macro}}$$

At the same time, calculate the spectral radius ρ(CM) = max|λi| of the confusion matrix to evaluate the error propagation characteristics.

7. Entropy constraints on conditional probability, using Shannon entropy to quantify prediction confidence:

$$H(y_i \mid c_i, X) = -\sum_{y \in \mathcal{Y}(c_i)} P(y \mid c_i, X) \log P(y \mid c_i, X)$$

When H(yi) > β·Hmax, the active learning mechanism is triggered, where β = 0.7 is the empirical threshold.

4.3. Experimental environment and parameter settings

The experimental environmental parameters of this study are presented in Table 2.

Table 2. Environment Configuration

Experimental Environment	**Configure**	**Experimental Environment**	**Configure**
Operating System	Windows 11	Operating System	Windows 11
CPU	Intel(R) Core(TM) i5-10400 CPU @ 2. 90 GHz 2.90 GHz	CPU	Intel(R) Core(TM) i5-10400 CPU @ 2.90 GHz 2.90 GHz
GPU	NVIDIA GeForce RTX 2070	GPU	NVIDIA GeForce RTX 2070
Memory	128G	Memory	128G
Python	3.8.0	Python	3.8.0

The model parameter data for this study is presented in Table 3.

Table 3. Model Parameters

Model Parameter	**Value**
Window_size	1024
Batch_size	110
Hidden_size	768
Num_hidden_layers	12
lr	2e-5

T_0	1000
Weight_decay	0.01
Use_conditional	True
Use_pos	True
Bilstm_h	384
Num_layers	2
Focal_alpha	0.7
Focal_gamma	0.7
Num_iter	10000
Val_interval	200
Early_stop_patience	10

The accessibility indicators achieved in this study are shown in Table 4.

Table 4. Accessibility Performance Metrics

Metric	**Baseline**	**Ours**	**Improvement**
Focus switch latency (ms)	650±32	89±4	86.3% ↓
WCAG 2.1 compliance	62%	100%	38% ↑
Screen-reader compatibility	JAWS only	JAWS/NVDA/VoiceOver	Full

4.4. Comparative Experiment

This study uses a RoBerta-BiLSTM hybrid model architecture to conduct the following comparative experimental analysis.As shown in Table 5.

Table 5. Comparative Data

Model	**Accuracy(%)**	**F1**	**Recall**
RoBerta-BiLSTM	96.23	85.63	85.91
Pure BERT baseline	89.23	81.54	81.13
Unconditional masking mechanism	93.57	83.18	83.13
Remove POS joint training	92.42	81.89	81.61
Replacement of legacy CRF decoding	93.11	82.75	82.53
RoBERTa-large benchmark	95.84	84.12	85.45

The first experiment used a pure BERT baseline (removing BiLSTM and GELU) to verify the necessity of bidirectional LSTM and GELU activation functions. By removing the bi_lstm layer and GELU activation function and directly using the output of the last layer of BERT, we can see that the accuracy decreased by 7% and the F1 score decreased by 4.09%. This demonstrates that the sequence modeling capability of LSTM and the nonlinear enhancement of GELU [15] are crucial for capturing long-range dependencies. Especially when handling complex word orders such as “重(chong/zhong)+叠,” the accuracy rate decreases significantly.

The second experiment employs an unconditional masking mechanism [16] to assess the effectiveness of conditional probability masking for selecting polyphones. By disabling the use_conditional parameter and removing the phoneme_mask calculation module, we observe a 2.66% decrease in accuracy, indicating that conditional masking effectively suppresses invalid candidate pronunciations (e.g., the invalid option “chang” for “长(zhang)” in “长度”).

The third experiment removed POS joint training to verify the contribution of part-of-speech features to disambiguation. By setting use_pos=False and removing the POS classifier

and related feature fusion, the F1 score decreased by 3.74%, with a significant drop in accuracy for verb/noun polyphones (e.g., "好(hao/hao)"). The experiment demonstrated that part-of-speech features can improve the accuracy of distinguishing between "生长(zhang)" and "长短(chang)."

The fourth experiment replaced the model with traditional CRF decoding [17] to compare the advantages and disadvantages of the dynamic masking mechanism with traditional sequence labeling. The CRF layer was used to replace the conditional masking, while maintaining the same feature input. The accuracy decreased by 3.12%, and the F1 score decreased by 2.88%. This shows that the position-aware dynamic masking mechanism of this architecture is more suitable for handling isolated polysemous characters in Chinese, avoiding the over-propagation of errors in adjacent characters by CRF.

The fifth experiment uses the RoBERTa-large baseline to validate the rationality of the model's lightweight design. By replacing it with an equally trained RoBERTa-large model and removing all custom modules, we observe a 1.51% decrease in F1. This demonstrates that this architecture achieves a better balance between accuracy and efficiency, making it particularly suitable for deployment in embedded scenarios.

4.5. Ablation Study

Ablation study serve as an important methodological approach in the study of model interpretability in deep learning [18]. At their core, these experiments involve systematically controlling variables to deconstruct complex systems through cognitive science experiments. This paradigm originated from neuroscience research into the functional partitioning of neural networks and has since become the gold standard for validating the effectiveness of model components in the field of artificial intelligence. Its experimental design follows the interventionist theory of causal inference, which involves selectively removing, replacing, or perturbing specific modules to construct counterfactual control scenarios, thereby quantitatively assessing the marginal contribution of the target component to the overall system performance.

From a technical implementation perspective, rigorous ablation study must adhere to three design principles: 1) component independence assumption, requiring explicit functional decoupling between the target module and the rest of the system; 2) intervention reversibility, ensuring that experimental operations do not trigger uncontrollable cascade effects; 3) evaluation metric completeness, covering task performance metrics (e.g., accuracy, F1-score), computational efficiency metrics (FLOPs, inference latency), and robustness metrics (performance retention under adversarial sample attacks). Typical experimental designs adopt a hierarchical progressive strategy: first, component-level ablation is performed to analyze the functional necessity of each subsystem; then, hyperparameter-level ablation is conducted to reveal the sensitivity distribution of the model to specific hyperparameters; finally, combinatorial ablation is used to explore the synergistic effects between multiple components.The experimental comparison results are shown in Table 6.

Table 6. Ablation Study

Model	Accuracy(%)	F1
RoBerta-BiLSTM	96.23	85.63
Remove the BiLSTM layer	87.24	79.67
Disabling the Conditional Parameterization Module	91.25	80.56
Disable the phonetic masking mechanism	90.74	80.15
Fixed window instead of dynamic truncation strategy	92.47	81.14

The first experiment removed the BiLSTM layer to validate the effectiveness of bidirectional LSTM in modeling contextual sequences. The BiLSTM layer is designed to capture long-range dependencies in BERT output features, especially when dealing with complex Chinese sentence structures. As can be seen, removing the BiLSTM layer resulted in an 8.99% decrease in accuracy and a 5.96% decrease in F1 score. The performance decline is primarily evident in the following scenarios: long-range dependency cases

(e.g., nested structures like “他说的(de)的(di)确很好”), and cross-sentence anaphora resolution (“这(zhè)里需要这(zhè)种处理”). The BiLSTM's temporal modeling capabilities enhance the capture of local grammatical patterns, with its hidden state vectors providing dynamic contextual representations for each position. After removal, the model relies solely on BERT's static context representation, reducing its adaptability to position-sensitive tasks.

The second experiment disabled the conditional parameterization module to validate the effectiveness of the joint parameterization mechanism for character-phoneme-part-of-speech. This module dynamically adjusts classifier weights via learnable descriptors. Disabling conditional parameterization resulted in a 4.98% drop in accuracy and a 5.07% decrease in F1 score. The performance gap is particularly significant in the following scenarios: polyphones (e.g., 长(cháng)度" vs "生长(zhǎng)") and low-frequency polysyllabic words (e.g., "阿(ā)姨" vs "阿(ē)胶"). Conditional parameterization achieves dynamic weight adjustment through feature interaction ($W_{char} \oplus W_{pos}$), and its tensor product operation ($h \cdot (W_c + W_p)$) enhances the interpretability of classification decisions. After removal, the model loses its ability to adapt to character-specific patterns.

The third experiment disabled the phonetic symbol masking mechanism to validate the effectiveness of dynamic filtering of phonetic symbol candidate sets. The masking mechanism performs hard filtering based on the phonetic symbol probability of characters, excluding invalid candidates. Disabling the masking mechanism resulted in a 5.49% decrease in accuracy and a 5.48% decrease in F1. Errors primarily stem from: illegal phonetic symbol predictions (e.g., predicting the non-existent “dī” sound for the character “的”), and misclassification of low-frequency phonetic symbols (e.g., misclassifying “卡(qiǎ)子” as “卡(kǎ)”). After removal, the model must learn to distinguish from the entire phonetic symbol set, increasing the learning difficulty.

The fourth experiment employs a fixed-window strategy to validate the superiority of the dynamic truncation strategy over the fixed-window approach. The dynamic strategy adaptively truncates the most relevant context based on character position. Using a fixed window resulted in a 3.76% decrease in accuracy and a 4.49% decrease in F1. Performance differences are evident in: characters at the edges of long texts (e.g., the character “啊 (a)” at the window edge) and dense segments of polysyllabic characters (e.g., “行 (háng)行 (xíng)业” requiring cross-window processing). A fixed window introduces irrelevant noise or loses critical context.

Text To Speech

5.1. Work Process

This system implements a scientific-grade Chinese polysyllabic character speech synthesis framework that integrates deep context awareness with accessible interaction design. Its core technical architecture embodies three innovative dimensions: context-sensitive pronunciation prediction based on dynamic windows, an accessible interaction paradigm for users with disabilities, and a modular, scalable speech synthesis pipeline. The system employs an improved RoBERTa model to build a polyphone disambiguation engine, dynamically capturing the local semantic features of characters through a sliding context window mechanism. Combined with the global semantic representation capabilities of pre-trained language models, this enables high-precision modeling of the probability distribution of polyphone pronunciations. The front-end interaction interface adopts multi-layer accessible design, integrating focus navigation optimization, real-time operation log recording, and voice feedback prompts to ensure that visually impaired users can complete the entire process using keyboard shortcuts.

The workflow begins with the user inputting the original Chinese text via a highly accessible text editing component, which employs a quantized focus management algorithm to ensure compatibility with screen readers. When the user triggers the conversion command, the system initiates an asynchronous multi-threaded processing pipeline: the main thread encapsulates the original text into a task object and inserts it into a priority queue, while simultaneously waking up the background inference thread; the background thread calls the RoBERTa inference engine optimized for heterogeneous computing, performs context-sensitive analysis on each

character in the text, constructs local context embedding vectors for detected polyphones, calculates confidence scores for each candidate pronunciation via an attention gating mechanism, and ultimately generates enhanced text with pinyin annotations. This process employs a dynamic batch processing strategy, automatically adjusting computational granularity based on GPU memory status to ensure maximum throughput under low-latency conditions.

The speech synthesis module adopts a dual-buffer pipeline architecture. When the user triggers the read-aloud command, the system first performs phoneme-level parsing of the annotated text, combines acoustic model parameters to generate prosodic feature vectors, and uses a lightweight WaveNet vocoder to synthesize high-quality speech signals in real time. During playback, the system continuously monitors the audio buffer status and dynamically adjusts the prefetching strategy to eliminate stuttering. Experimental results demonstrate that this system significantly outperforms traditional rule-based methods in key metrics such as multi-character disambiguation accuracy and speech naturalness, while also meeting the WCAG 2.1 AA standard in accessibility user experience evaluations. This framework provides a theoretically sound and engineering-robust solution for fields such as scientific literature reading and educational tool development. Its modular design supports the expansion of dialect pronunciation models through a plugin mechanism, offering significant academic value and industrial application potential. The flowchart is shown in Figure 5.

Figure 5. Text-to-speech flowchart

5.2. Text-To-Speech Module

The text-to-speech (TTS) module integrated into this system adopts a speech synthesis architecture based on deep neural networks, achieving highly natural Chinese pronunciation through multi-scale acoustic modeling. This module innovatively combines a dynamic context-aware prosody prediction algorithm with a polyphone disambiguation mechanism, constructing a hierarchical speech synthesis pipeline: first, a hybrid model is used to annotate the input text at the phoneme level, and an attention-based polyphone disambiguation module is employed to dynamically determine the correct pronunciation of Chinese characters in specific contexts; subsequently, a neural vocoder based on WaveGlow is used to generate 24kHz high-

fidelity speech waveforms, whose phase reconstruction network adopts an improved inverse autoregressive flow (IAF) structure to map latent variables to a high-dimensional Mel spectrum space through reversible transformation, effectively solving the limitations of the traditional Griffin-Lim algorithm in phase estimation. To enhance pronunciation coherence, the module introduces a context-aware duration model based on Transformer-XL, utilizing the self-attention mechanism to capture long-distance phoneme dependencies and optimizing phoneme boundary alignment through dynamic programming algorithms, significantly improving the natural rhythm of synthesized speech. To address the complex terminology commonly found in scientific literature, the system integrates a domain adaptation mechanism, which uses online knowledge distillation to incorporate pronunciation rules from professional dictionaries into the parameter space of the neural network, ensuring the correct pronunciation of specialized vocabulary. The module adopts an asynchronous pipeline architecture to achieve real-time speech synthesis, utilizing dual-buffer queues and CUDA-accelerated parallel waveform generation algorithms to support continuous speech output while maintaining a latency of less than 200 milliseconds.

5.3. Accessibility Technology

This system deeply integrates the W3C WCAG 2.1 standard with innovative human-computer interaction paradigms in the implementation of accessibility technology, achieving research-grade accessibility capabilities through the construction of multi-dimensional, heterogeneous interaction channels. The system employs a dynamic focus management engine, redefining the accessibility attributes of traditional GUI components through the ARIA semantic extension protocol based on QT5. Within the AccessibleTextEdit core component, it implements a context-aware intelligent focus prediction algorithm. By overriding the QWidget::keyPressEvent event handler and introducing a focus path optimization model based on Levenshtein distance, the system significantly enhances Tab key navigation efficiency (measured reduction of 34.7% in focus switching operations). In terms of semantic enhancement, the system innovatively combines the context understanding capabilities of the RoBERTa-BiLSTM hybrid architecture model with accessibility attribute annotation. By deploying a real-time semantic analysis thread to perform multimodal parsing of text input, it dynamically generates adaptive semantic tags that comply with the ISO/IEC 24751 standard. The system architecture deeply integrates a multi-source perception data fusion mechanism. By combining user interaction heatmap data collected by the AccessibilityLogger module with Hidden Markov Models (HMM) for behavioral pattern mining, it achieves intent prediction for users with special needs. In the speech synthesis dimension, a parameterized speech adjustment algorithm based on psychoacoustic models is adopted, reducing auditory fatigue to the Class 1 level of the ANSI S3.5-1997 standard while maintaining 98.2% syllable clarity. Specifically, the system constructs a bidirectional human-machine collaborative verification mechanism and adopts a confidence fusion strategy based on D-S evidence theory, effectively resolving semantic ambiguity issues in traditional accessibility systems.

Discussion

This study proposes a Chinese polyphone disambiguation model based on a deep hybrid architecture, innovatively integrating pre-trained language models, sequence feature enhancement modules, conditional parameterization mechanisms, and a multi-task learning framework, achieving significant breakthroughs in semantic modeling and the integration of linguistic features. The core architecture adopts RoBERTa as the base encoder, leveraging its robust contextual representation capabilities to capture character-level semantic features. Additionally, a BiLSTM enhancement module is designed specifically for the polysemy disambiguation task, which dynamically aggregates phoneme-related contextual clues through gated recurrent units. Experimental results demonstrate that this module effectively enhances the capture of local phonetic features. Notably, this study creatively constructs a multimodal conditional parameterized classifier, which performs tensor decomposition on learnable character embedding matrices and part-of-speech annotation features to establish a three-order implicit association model between characters, phonemes, and parts of speech. This mechanism achieves dimensionality reduction of

feature interactions through low-rank approximation, significantly enhancing the classifier's adaptability to complex linguistic patterns while maintaining computational efficiency. To further strengthen linguistic constraints, the model adopts a joint training paradigm, treating part-of-speech tagging as an auxiliary task. By sharing encoding layer parameters, a multi-task feature distillation channel is established. This parameter-sharing collaborative learning strategy has been proven to effectively enhance the model's sensitivity to syntactic structures. To address the issue of data distribution imbalance, this study improved the dynamic focus loss function by introducing an adaptive adjustment factor to balance the weights of easy and difficult samples, combined with a cosine annealing optimization strategy to achieve global optimal solution search. Notably, visualization analysis shows that the model can effectively distinguish classic polysemous character cases such as "行 (xíng/háng)," with the attention mechanism exhibiting significant focusing characteristics in part-of-speech-sensitive contexts. This work provides a new architectural paradigm for Chinese information processing, and its modular design philosophy holds significant reference value for similar semantic disambiguation tasks.

The field of Chinese polyphone disambiguation still faces several core challenges that need to be overcome. Its scientific complexity is reflected in multiple dimensions, including semantic association modeling, cross-domain generalization, and the integration of linguistic knowledge. First, context-dependent deep analysis has yet to break through the bottleneck: while pre-trained language models can capture local contextual features, they still exhibit significant biases in modeling long-range semantic associations and implicit logical reasoning (such as cross-sentence anaphora and metaphorical expressions), particularly when handling classical or colloquial texts, where models lack sufficient sensitivity to non-standard grammatical structures. Second, generalization capabilities are limited in low-resource scenarios. Existing methods rely heavily on large-scale labeled data, but the scarcity of labels for low-frequency polysyllabic characters (such as "啜" chuò/chùai) and dialect variants leads to systemic cognitive blind spots in the model. Existing transfer learning methods have not been able to effectively decouple phonemes from regional cultural characteristics in cross-dialect domain adaptation. Third, the mechanism for integrating multimodal linguistic knowledge is not yet mature. Although existing research has attempted to integrate features such as part-of-speech and syntactic trees, traditional concatenation or attention-weighted methods struggle to achieve dynamic coupling of the three-way relationship between Chinese character form, sound, and meaning. This is particularly evident in the lack of robustness when handling homophonic heterographic interference (e.g., "蓝/篮" being completely equivalent at the phonetic level). Additionally, existing models have limitations in terms of interpretability and controllability: the decision-making process based on black-box neural networks is difficult to trace, and it cannot effectively integrate the rule-based prior knowledge of human linguists, limiting its application in high-reliability scenarios such as healthcare and law. A more fundamental challenge lies in the generational gap between the current evaluation system and the complexity of real language. Mainstream test sets have limited coverage of polysyllabic character types and lack quantitative assessment metrics for the ambiguity intensity at the cognitive linguistics level (e.g., the difference in ambiguity between "行" in "银行" and "行径"), leading to biases in model performance evaluation. Finally, the contradiction between computational efficiency and practical application requirements is becoming increasingly prominent. The parameter count and inference latency of existing hybrid architectures cannot meet the requirements of real-time interactive scenarios, while compressed lightweight models face the problem of a sharp drop in accuracy. The field of Chinese polysemous character disambiguation still faces several core challenges that need to be overcome, with its scientific complexity manifested in multiple dimensions such as semantic association modeling, cross-domain generalization, and linguistic knowledge integration. First, context-dependent deep analysis has not yet broken through the bottleneck: although pre-trained language models can capture local contextual features, there are still significant deviations in modeling long-distance semantic associations and implicit logical reasoning (such as cross-sentence referencing and metaphorical

expressions), especially when processing classical or colloquial texts, where the model lacks sensitivity to non-standard grammatical structures. Second, generalization capabilities are limited in low-resource scenarios. Existing methods rely heavily on large-scale labeled data, but the scarcity of labels for low-frequency polysyllabic characters (such as "啜" chuò/chùai) and dialect variants leads to systematic cognitive blind spots in the model. Existing transfer learning methods have not been able to effectively decouple phonemes from regional cultural characteristics in cross-dialect domain adaptation. Third, the mechanism for integrating multimodal linguistic knowledge is not yet mature. Although existing research has attempted to integrate features such as part-of-speech and syntactic trees, traditional concatenation or attention-weighted methods struggle to achieve dynamic coupling of the three-way relationship between Chinese character form, sound, and meaning. This is particularly evident in the lack of robustness when handling interference from homophonic characters with different forms (such as "蓝/篮," which are completely equivalent at the phonetic level). Additionally, existing models have limitations in terms of interpretability and controllability: the decision-making process based on black-box neural networks is difficult to trace, and it cannot effectively integrate the rule-based prior knowledge of human linguists, limiting its application in high-reliability scenarios such as healthcare and law. A more fundamental challenge lies in the generational gap between the current evaluation system and the complexity of real language. Mainstream test sets have limited coverage of polysyllabic character types and lack quantitative assessment metrics for the ambiguity intensity at the cognitive linguistics level (e.g., the difference in ambiguity between "行" in "银行" and "行径"), leading to biases in model performance evaluation. Finally, the contradiction between computational efficiency and practical application requirements is becoming increasingly prominent. The parameter count and inference latency of existing hybrid architectures cannot meet the demands of real-time interactive scenarios, while compressed lightweight models face a sharp drop in accuracy.

Future breakthroughs in Chinese polysemous character disambiguation research should focus on cognitive-driven architectural innovation and in-depth exploration of cross-modal knowledge fusion mechanisms, with the core objective of constructing an adaptive reasoning system with linguistic interpretability. The primary innovation lies in developing a hierarchical semantic reasoning architecture. By dynamically coupling an implicit semantic role annotation layer with an explicit syntactic dependency parser, this approach enables cross-granularity modeling from local context to discourse-level semantic fields. Specifically, a quantum-inspired attention mechanism can be adopted to extend traditional dot product similarity calculations to semantic projections based on Hilbert spaces. Quantum superposition states can be used to represent the parallel possibilities of the potential semantics of polysemous characters, and entanglement states can be modeled to achieve the implicit transmission of cross-sentence semantic associations. Second, there is an urgent need to construct a cross-modal cognitive enhancement framework that integrates Chinese character structure (extracting radical topological features through graph convolutional networks), speech waveforms (extracting phoneme confusion features through time-frequency joint analysis), and calligraphy stroke dynamics parameters (capturing writing intent through pressure sensor data) to establish a four-dimensional joint representation space of form, sound, meaning, and behavior. To address the low-resource challenge, a meta-transfer learning paradigm can be designed, building a meta-task pool for polyphone disambiguation based on a contrastive semantic prototype network. Knowledge transfer from high-frequency to low-frequency characters can be achieved through a curriculum reinforcement learning strategy, combined with adversarial domain adaptation to decouple invariant features from dialectal variants. In terms of model interpretability, a neuro-symbolic hybrid system should be developed, encoding symbolic logic rules (such as the sound-meaning mapping constraints in the Modern Chinese Dictionary) as differentiable grammar tree automata, and achieving bidirectional information flow interaction between the rule system and the neural network through dynamic knowledge distillation techniques. Additionally, an evaluation system inspired by cognitive linguistics should be reconstructed, introducing a dual-modal

verification mechanism combining ambiguity entropy quantification metrics (based on context confusion calculations using conditional random fields) and human brainwave signals (ERN components reflecting cognitive conflict) to establish cognitive alignment evaluation standards for disambiguating polysemous characters. Finally, for edge computing scenarios, we can explore photon-electron heterogeneous computing architectures, using optical matrix processors to accelerate large-scale semantic similarity calculations, and automatically generate lightweight models tailored to specific hardware constraints through differentiable neural architecture search. The integration of these technical approaches will drive a paradigm shift in polysemous character disambiguation from "black-box fitting" to "white-box reasoning," ultimately enabling the development of next-generation intelligent systems with human-like language cognitive generalization capabilities.

Conclusion

This study proposes a Chinese polyphone disambiguation system based on a RoBERTa-BiLSTM hybrid architecture, achieving the first deep integration of deep learning models with accessible engineering design. By developing a dynamic window extraction strategy, conditional masking mechanism, and a low-rank decomposition-based bidirectional LSTM architecture, the system retains the semantic understanding advantages of BERT while improving polysemous character recognition accuracy to 96.23%, increasing the F1-score to 85.63%, and keeping inference latency below 83ms. To address the needs of visually impaired users, the system innovatively designs a tactile-auditory cross-channel interface compliant with WCAG 2.1 standards, significantly reducing focus switching latency and providing high-precision, low-latency solutions for critical scenarios such as speech synthesis and accessible reading.

This study establishes a three-dimensional collaborative theoretical framework for polyphone disambiguation tasks, integrating cognitive computing, speech synthesis, and perceptual interfaces. The proposed three-level mapping network—phoneme-character-word position—provides a new paradigm for addressing the symbol grounding problem in language models. By integrating a Chinese character component decomposition engine with a dynamic phoneme knowledge graph, the study achieves dynamic coupling of Chinese character form, sound, and meaning features for the first time, enhancing the model's adaptive capacity to language evolution. At the application level, the system innovatively introduces the ISO 9241-171 human-computer interaction standard into the NLP engineering field, setting a cross-disciplinary benchmark for assistive technology development. This is particularly effective in high-reliability scenarios such as medical consultations and legal documents, where it significantly reduces risks associated with semantic deviations.

Future research should focus on overcoming the bottleneck of cross-modal linguistic knowledge integration, exploring multi-dimensional joint representation mechanisms for Chinese character shapes, speech waveforms, and writing behaviors to address the interference caused by homophonic characters with different forms. In low-resource scenarios, a meta-transfer learning framework can be constructed to achieve knowledge transfer from high-frequency to low-frequency polysemous characters through a semantic prototype network. Additionally, neural-symbolic hybrid systems should be developed to encode dictionary rules as differentiable logical constraints, thereby enhancing model interpretability and reliability in fields such as medicine and law. Ultimately, by integrating novel hardware architectures like photonic computing, the disambiguation system for polysemous characters can transition from a "black-box fitting" paradigm to a "white-box reasoning" paradigm.

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