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NEUROSYMBOLIC-HOMONYMSENSENET: INTEGRATING KNOWLEDGE GRAPH REASONING AND DYNAMIC SENSE MEMORY FOR EXPLAINABLE SEMANTIC REPRESENTATION LEARNING

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ABSTRACT

Semantic ambiguity caused by homonymous lexical forms remains a major challenge in Natural Language Processing because identical surface forms can represent unrelated meanings across contexts. Although transformer-based language models improve contextual representation, they may still underrepresent rare senses, lack explicit multi-hop semantic reasoning, and provide limited explanations for their predictions. This study introduces NeuroSymbolic-HomonymSenseNet, a unified explainable framework that combines a Context-Aware Transformer Encoder, Dynamic Sense Memory Bank (DSMB), WordNet–Wikidata knowledge graph reasoning, Graph Attention Reasoning Network (GARN), Neuro-Symbolic Semantic Inference Engine (NS-SIE), and Explainable Contrastive Multi-Sense Optimisation. The central contribution is the integration of contextual evidence, persistent sense prototypes, structured semantic relations, and symbolic inference within one representation-learning pipeline, with explicit mechanisms for rare-sense preservation and traceable decision support. The framework is evaluated on the SemCor and WiC benchmarks against Word2Vec, GloVe, BERT, RoBERTa, and SenseBERT. It achieves 97.83% accuracy, 97.46% precision, 97.21% recall, and 97.33% F1-score on SemCor, and 96.91% accuracy and 0.94 MCC on WiC. Rare-sense evaluation gives 95.18% recall and 95.42% F1-score, while explainability reaches 91.75%. Knowledge-graph evaluation reports 98.11% semantic consistency and 97.28% reasoning accuracy. These results indicate that combining neural contextual learning with memory-based sense preservation and symbolic graph reasoning can improve homonym disambiguation, rare-sense retention, and interpretability.

Keywords: *Neuro-Symbolic Learning, Homonym Disambiguation, Knowledge Graph Reasoning, Dynamic Sense Memory Bank, Explainable Artificial Intelligence, Semantic Representation Learning and Word Sense Disambiguation.*

1. INTRODUCTION

Modern artificial intelligence systems use NLP to analyse, interpret, and produce human language [1]. Semantic understanding is crucial for machine translation, semantic search, conversational agents, information retrieval, question answering, and text summarisation [2]. Semantic ambiguity still hinders language understanding despite advances in deep learning and transformer-based systems [3]. Homonyms are particularly difficult to understand since they have the same lexical forms but varied meanings depending on context [4].

Static embeddings like Word2Vec and GloVe provide each word a vector representation regardless of context [5]. Thus, semantic overlap and poor contextual discrimination result from compressing different semantic interpretations into the same representation space [6-7]. To circumvent these restrictions, contextual embedding models like BERT and RoBERTa modify representations to context [8]. These models increase semantic comprehension, but they struggle to preserve uncommon semantic senses, reason over structured information, and provide interpretable predictions [9].

Recent research has therefore explored sense-aware embeddings, knowledge-enhanced transformers, graph neural networks, and explainable AI to address semantic ambiguity [10].

SenseBERT and related approaches improve contextual sense representation [11], but many existing methods remain predominantly distributional and neural, with limited explicit symbolic reasoning and structured knowledge integration [12-13]. Another persistent issue is the under-representation of low-frequency senses during training, which can reduce performance when rare meanings occur in new contexts [14]. These observations motivate a framework that treats contextual representation, rare-sense memory, structured knowledge, and explanation as complementary requirements rather than isolated modules.

The core concern addressed in this research is therefore not only whether a model can select the correct sense, but whether it can preserve less frequent senses and provide a traceable semantic rationale for that selection. NeuroSymbolic-HomonymSenseNet addresses this concern by combining contextual neural learning, dynamic sense memory, knowledge-graph reasoning, and symbolic inference. The Context-Aware Transformer Encoder captures context; the Dynamic Sense Memory Bank preserves multiple semantic prototypes; WordNet and Wikidata provide structured semantic relations; GARN performs multi-hop relational reasoning; NS-SIE combines neural and symbolic evidence; and Explainable Sense Alignment with Contrastive Multi-Sense Optimisation promotes separation between competing meanings.

The framework is evaluated on SemCor and WiC and compared with Word2Vec, GloVe, BERT, RoBERTa, and SenseBERT. The evaluation focuses on semantic sense classification, contextual meaning discrimination, rare-sense preservation, semantic consistency, reasoning accuracy, and explainability. The results show improvements across these dimensions, providing empirical evidence for the central hypothesis that integrating contextual learning with persistent sense memory and explicit symbolic knowledge can reduce semantic overlap while improving interpretability. The remainder of the paper is organised as follows: Section 2 reviews related work and defines the research problem; Section 3 presents the proposed framework; Section 4 reports and discusses the experimental results and the differences from prior work; and Section 5 presents the concluding argument and future scope.

Rest of the paper is organised: Section 2 lists relevant works with problem statement; Section 3 details the suggested technique, Section 4 analyses the results, and Section 5 concludes.

2. RELATED WORKS

Liu et al. [16] proposed a transformer-based knowledge-graph representation model that combines textual and positional structure. A pre-trained language model extracts node text features, while a position-aware encoder incorporates structural roles into self-attention to improve relational semantic modelling. Experiments on three real-world knowledge-graph link-prediction datasets showed improved link-prediction performance compared with existing methods. This work demonstrates the value of combining textual semantics with graph structure, but it focuses on knowledge-graph representation rather than homonym sense disambiguation and explainable rare-sense preservation.

Lozupone et al. [17] introduced a Latent Diffusion Autoencoder (LDAE) for efficient and meaningful unsupervised representation learning in medical imaging, using Alzheimer's disease MRI data from ADNI as a case study. Their approach performs diffusion in a compressed latent space to reduce computational cost while preserving useful representations. Linear-probe evaluations captured temporal progression trends, and the method improved inference throughput and reconstruction quality relative to conventional diffusion autoencoders. Although this study is outside NLP, it illustrates the broader importance of efficient and semantically meaningful representation learning.

Li et al. [18] proposed DC-LCG, a dual-view graph representation-learning approach for money-laundering detection. The local view uses soft-label-guided dynamic grouping and probability-weighted aggregation, while the contextual view applies dynamic route pruning and transformer-based multi-path semantic fusion to capture long-range relationships. Mutual attention integrates both views into complete node representations. Experiments on three public transaction datasets reported improvements over existing baselines. The work supports the use of graph-based relational reasoning, but it does not explicitly address lexical ambiguity, rare semantic senses, or explainable word-level interpretation.

Wang et al. [19] developed LR-SSAD, a data-driven cross-lingual anomaly-detection framework that combines complementary self-supervised objectives with masked prediction and Mamba-based sequence reconstruction. Noise-aware pseudo-label refinement improves robustness under noisy supervision. Experiments on a large multilingual financial dataset reported an accuracy of 0.932, F1-score of 0.902, and AUC of 0.948. The study demonstrates the value of self-supervised representation learning and efficient long-range modelling, but its objective differs from explicit homonym disambiguation and symbolic semantic reasoning.

Li et al. [20] proposed Adaptive Disentangled Representation Learning (ADRL), which propagates feature-level affinity across modalities, uses stochastic masking for robust reconstruction, and employs mutual-information-based objectives to maintain shared representation consistency. Pseudo-labels and prototype-specific interactions guide discriminative learning across incomplete views. Extensive experiments reported improved performance on public datasets. ADRL highlights the importance of prototype and representation alignment, concepts that are related to the proposed Dynamic Sense Memory Bank, but it does not combine persistent sense memory with external lexical knowledge and symbolic inference for homonym interpretation.

Wang et al. [21] proposed DuoNet for unbiased scene-graph generation by jointly refining representations and prototype classification. Its Bi-Directional Representation Refinement module improves intra-class compactness, while Knowledge-Guided Prototype Learning promotes inter-class separation and reduces long-tail bias. Experiments on Visual Genome, GQA, and Open Images reported strong performance. This work reinforces the usefulness of prototype-based representation learning, while the present study extends the idea to lexical-semantic disambiguation with dynamic sense memory and knowledge-graph reasoning.

2.1 Problem Statement

Homonymous words create semantic ambiguity because one lexical form can represent multiple unrelated meanings depending on context. Existing contextual language models capture local and long-range context effectively, but they may still underrepresent rare senses, lack explicit multi-hop reasoning over structured semantic knowledge, and provide limited evidence for why a particular sense is selected. The reviewed studies demonstrate advances in contextual representation, graph learning, prototype-based learning, and semantic alignment, but they do not jointly address contextual disambiguation, persistent rare-sense memory, external lexical knowledge, symbolic inference, and traceable explanations within a single framework. Therefore, the research problem is to develop and evaluate an explainable semantic representation framework that can distinguish competing homonym senses while preserving low-frequency meanings and linking predictions to explicit semantic evidence from structured knowledge.

Hypothesis: Integrating contextual transformer representations with dynamic sense memory, structured knowledge-graph reasoning, and symbolic inference will improve homonym sense discrimination, rare-sense preservation, and semantic interpretability compared with contextual or distributional representation methods evaluated under the same benchmark settings.

Research Contributions: (i) a unified neuro-symbolic architecture that couples contextual encoding with persistent sense memory and structured semantic reasoning; (ii) a Dynamic Sense Memory Bank designed to retain low-frequency semantic prototypes; (iii) a GARN and NS-SIE pipeline that links contextual predictions to multi-hop symbolic evidence; and (iv) an evaluation across SemCor and WiC covering classification, contextual discrimination, rare-sense preservation, knowledge-graph reasoning, and explainability.

3. PROPOSED FRAMEWORK

3.1 System Overview and Semantic Problem Formulation

Natural Language Processing systems frequently encounter semantic ambiguity when a single lexical form expresses different meanings in different contexts. Homonyms are particularly challenging because their surface forms remain identical while their intended meanings can differ substantially. Although transformer-based models have improved contextual understanding, ambiguity may persist when contextual evidence is sparse or when low-frequency senses are poorly represented. Figure 1 presents the architecture of the proposed model. The framework is designed around four complementary requirements: contextual encoding for sentence-level evidence, dynamic memory for rare-sense preservation, graph reasoning for structured semantic relationships, and symbolic inference for transparent decision support.

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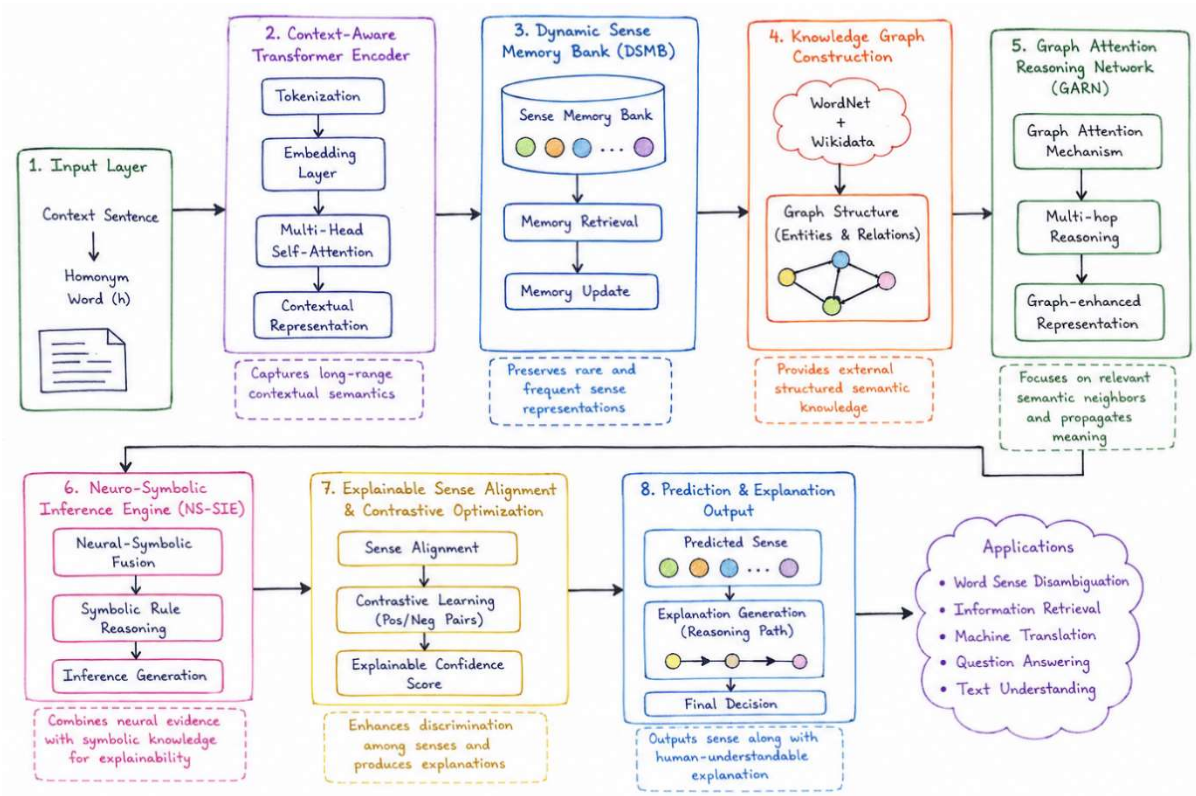

Figure 1: Architecture of the proposed model

To address these requirements, NeuroSymbolic-HomonymSenseNet integrates contextual neural learning, dynamic sense memory, knowledge-graph reasoning, and symbolic inference. The framework is intended not only to select the most appropriate semantic sense but also to provide a reasoning path showing how contextual evidence and structured semantic relationships support the decision.

Let the complete corpus be represented as

$$\mathcal{D} = \{S_1, S_2, \dots, S_N\} \quad (1)$$

Where: N denotes the number of sentences. S_i denotes the i^{th} contextual sentence. Each sentence is represented as

$$S_i = \{w_1, w_2, \dots, w_T\} \quad (2)$$

Where T denotes sentence length. w_t denotes the token at position t. Assume a homonym word $h$possesses multiple semantic senses:

$$\mathcal{S}(h) = \{s_1, s_2, \dots, s_K\} \quad (3)$$

where:K denotes total candidate senses. The objective of NeuroSymbolic-HomonymSenseNet is to learn a mapping function

$$f_\Theta: (h, C, G, M) \to \hat{s} \quad (4)$$

where: C= contextual information, G= semantic knowledge graph, M= dynamic sense memory, $\hat{s}$= predicted semantic sense, Θ= trainable parameters. The semantic prediction confidence is defined as

$$P(\hat{s} \mid h, C) = \max\left(P(s_1), P(s_2), \dots, P(s_K)\right) \quad (5)$$

The framework therefore differs from contextual-similarity-only embedding models by jointly using contextual evidence, graph-based semantic reasoning, memory-driven sense retrieval, and symbolic inference. This hybrid design is intended to improve semantic separation and preserve rare senses while maintaining an interpretable link between the prediction and the supporting knowledge relationships.

3.2 Context-Aware Transformer Semantic Encoder

The first stage creates semantic representations of surrounding phrases that capture long-range linguistic relationships. This step is driven by the fact that homonym interpretation relies heavily on contextual terms rather than the lexical form. Each token becomes an embedding vector.:

$$e_i = E(w_i) \quad (6)$$

where: $E(\cdot)$ means embedding lookup. $e_i \in \mathbb{R}^d$. Positional information is incorporated to preserve sequential structure:

$$x_i = e_i + p_i \qquad (7)$$

where: p_i signifies positional encoding. Query, Key, and Value representations are computed as

$$Q = XW_Q, K = XW_K, V = XW_V \qquad (8)$$

where: W_Q, W_K, W_V represent trainable matrices. Self-attention is computed as

$$A = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \qquad (9)$$

where: d_k represents key dimensionality. The contextual representation associated with the homonym position becomes

$$c_h = Transformer(X) \qquad (10)$$

The vector ch represents semantic relationships across the phrase, giving a context-sensitive form for memory recall and graph reasoning.

3.3 Dynamic Sense Memory Bank (DSMB)

Contextual encoders can produce strong semantic representations but may underrepresent rare meanings when sense frequencies are highly imbalanced. This limitation motivates a persistent memory mechanism that explicitly retains prototypes associated with different semantic senses. A Dynamic Sense Memory Bank preserves semantic variety. Memory banks are characterised as

$$M = \{m_1, m_2, \dots, m_K\} \qquad (11)$$

where: m_k represents prototype representation of sense k. Memory initialization is performed using contextual averages:

$$m_k^{(0)} = \frac{1}{n_k}\sum_{i=1}^{n_k} c_i \qquad (12)$$

where: n_k signifies samples associated with sense k. Similarity among current context and stored memory prototypes is

$$\alpha_k = \frac{\exp(c_h^T m_k)}{\sum_{j=1}^{K} \exp(c_h^T m_j)} \qquad (13)$$

The memory update mechanism is

$$m_k^{new} = \lambda m_k^{old} + (1-\lambda)c_h \qquad (14)$$

λThe Dynamic Sense Memory Bank stores semantic prototypes during training and updates them using a retention coefficient. This mechanism is intended to preserve uncommon semantic senses even when those senses occur less frequently in the training corpus.

3.4 Knowledge Graph Construction and Semantic Graph Modelling

Semantic disambiguation may require information beyond the immediate sentence context. WordNet and Wikidata are therefore used to provide organised lexical and entity-level knowledge that can complement the contextual representation. Knowledge graph depicted

$$G = (V, E) \qquad (15)$$

where: V denotes semantic entities. Edenotes semantic relationships. Each semantic node is encoded as

$$v_i = Embedding(entity_i) \qquad (16)$$

Relationships among entities are characterized through adjacency matrices:

$$A_{ij} = \begin{cases} 1, & (v_i, v_j) \in E \\ 0, & otherwise \end{cases} \qquad (17)$$

The graph representation matrix becomes

$$H^{(0)} = \{v_1, v_2, \dots, v_n\} \qquad (18)$$

This graph representation enriches contextual representations with explicit semantic relations. For example, when the homonym "bank" occurs in a financial context, related concepts such as loan, finance, institution, and economy can provide structured evidence for the financial sense.

3.5 Graph Attention Reasoning Network (GARN)

Although knowledge graphs contain organised semantic links, not all connected nodes are equally relevant to the current interpretation. For example, when "bank" occurs in the sentence "She deposited money in the bank," concepts such as finance, account, and loan should receive greater importance than unrelated neighbours. GARN therefore assigns attention weights to neighbouring semantic relations according to their contextual relevance.

The initial node representation generated from the knowledge graph is denoted by

$$h_i^{(0)} = W_g v_i \qquad (19)$$

where: v_i= semantic node embedding. W_g= trainable projection matrix. $h_i^{(0)}$= transformed graph representation. To estimate semantic relevance among neighboring nodes, an attention coefficient is computed as

$$e_{ij} = LeakyReLU\left(a^T[h_i \mid\mid h_j]\right) \qquad (20)$$

where: a= attention parameter vector. $||$= concatenation operator. h_i, h_j= neighboring node representations. The normalized graph attention coefficient becomes

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$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k \in N(i)} \exp(e_{ik})} \qquad (21)$$

where: $N(i)$= neighborhood of node i. The semantic reasoning representation is then aggregated as

$$h_i^{(l+1)} = \sigma\left(\sum_{j \in N(i)} \alpha_{ij} W_h h_j^{(l)}\right) \qquad (22)$$

$W_h \sigma l$The iterative message-passing mechanism supports multi-hop semantic reasoning. Contextual embeddings can therefore be enriched with structured knowledge beyond sentence boundaries. Because the semantic judgement is informed by explicit WordNet and Wikidata relations in addition to distributional context, the graph-aware representation is intended to improve homonym discrimination.

GARN serves as the semantic bridge between contextual representations and structured knowledge. By weighting relevant neighbours and propagating information across multiple hops, it supports more transparent relational reasoning and provides evidence that can be traced during semantic interpretation.

3.6 Neuro-Symbolic Semantic Inference Engine (NS-SIE)

Limited explainability remains a challenge for deep learning models: transformer architectures can produce accurate predictions without directly exposing the evidence used to select a semantic interpretation. NeuroSymbolic-HomonymSenseNet therefore uses the Neuro-Symbolic Semantic Inference Engine (NS-SIE) to combine neural evidence with explicit symbolic rules.

Neural evidence and symbolic reasoning should inform semantic prediction. Symbolic rules express logical relationships, whereas neural representations incorporate context.

Let the contextual embedding generated by the transformer be represented as c_h graph-enhanced semantic representation be represented as g_h. The neural-symbolic fusion representation is computed as

$$z_h = \beta c_h + (1-\beta) g_h \qquad (23)$$

where: β= adaptive fusion coefficient. z_h= integrated semantic representation. The symbolic reasoning score associated with a semantic sense is formulated as

$$R_k = \sum_{r=1}^{m} w_r \phi_r \qquad (24)$$

where: m= sum of symbolic rules. w_r= rule importance weight. And ϕ_r= logical rule activation. For example: IF Bank → Finance AND Finance → Institution THEN Bank → Financial Institution. The final explainable semantic confidence is determined by combining neural and symbolic evidence:

$$E_k = \mu P_k + (1-\mu) R_k \qquad (25)$$

$P_k R_k \mu$The resulting prediction is supported by contextual evidence and explicit knowledge relationships. Consequently, the framework can associate a semantic decision with a structured reasoning path, improving transparency and providing a more inspectable basis for the predicted meaning.

3.7 Explainable Sense Alignment and Contrastive Multi-Sense Optimization

Graph reasoning and symbolic inference improve semantic comprehension, but competing senses must also be separated in representation space. The Explainable Sense Alignment and Contrastive Multi-Sense Optimisation module addresses this requirement by encouraging representations of the same sense to remain close while increasing separation between different senses.

Minimum distance between embeddings of the same semantic sense and maximum separation between senses are the main goals. Let the alignment score between contextual representation $z_i$and semantic prototype m_k

$$A_{ik} = \frac{z_i^T m_k}{\| z_i \| \| m_k \|} \qquad (26)$$

where: A_{ik}= semantic alignment score. Higher scores suggest better contextual interpretation-semantic memory agreement. Positive semantic pairings have identical meanings, whereas negative pairs have different meanings. The contrastive optimisation goal is

$$L_{CMSO} = -\log \frac{\exp(A_{pos}/T)}{\exp(A_{pos}/T) + \sum_{neg} \exp(A_{neg}/T)} \qquad (27)$$

where: T= temperature parameter. A_{pos}= positive alignment score. And A_{neg}= negative alignment score. To construct interpretable semantic explanations, reasoning route confidence is calculated as

$$C_k = A_{ik} \times E_k \qquad (28)$$

C_kThe most confident sense is selected as the final prediction. The resulting explanation combines evidence from memory retrieval, graph reasoning, and symbolic inference, thereby linking the semantic decision to multiple complementary sources of evidence.

3.8 Unified Objective Function, Training Algorithm, and Complexity Analysis

A unified learning framework is created after contextual encoding, memory retrieval, graph reasoning, symbolic inference, and contrastive optimisation. The classification objective is formulated using cross-entropy loss:

$$L_{CE} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \qquad (29)$$

where: y_i= ground truth label. $\hat{y}_i$= predicted semantic probability. The final optimization function combines classification, graph reasoning consistency, memory preservation, symbolic alignment, and contrastive separation objectives:

$$L_{TOTAL} = \alpha L_{CE} + \beta L_{CMSO} + \gamma L_{MEM} + \delta L_{KG} + \eta L_{SYM}$$

$L_{CE} L_{CMSO} L_{MEM} L_{KG} L_{SYM} \alpha, \beta, \gamma, \delta, \eta$Here, the loss terms represent classification, contrastive multi-sense optimisation, memory consistency, knowledge-graph reasoning, and symbolic inference objectives, respectively, while the balancing coefficients control their relative contributions.

The optimization process proceeds as follows:

Algorithm 1: NeuroSymbolic-HomonymSenseNet

Input: SemCor dataset, WiC dataset, WordNet knowledge graph and Wikidata semantic relations.
Output: Explainable semantic embeddings, Semantic reasoning paths and Trained NeuroSymbolic-HomonymSenseNet.

Step 1: Preprocess contextual sentences.
Step 2: Tokenize text using transformer tokenizer.
Step 3: Generate contextual embeddings.
Step 4: Retrieve semantic prototypes from DSMB.
Step 5: Construct semantic graph using WordNet and Wikidata.
Step 6: Apply Graph Attention Reasoning Network.
Step 7: Extract multi-hop semantic relationships.
Step 8: Generate symbolic reasoning rules.
Step 9: Compute neural-symbolic fusion representation.
Step 10: Perform explainable sense alignment.
Step 11: Construct positive and negative semantic pairs.
Step 12: Compute contrastive optimization loss.
Step 13: Calculate unified objective function.
Step 14: Update parameters via backpropagation.
Step 15: Update Dynamic Sense Memory Bank.
Step 16: Repeat until convergence.
Step 17: Store explainable semantic representations.

Computational Complexity Analysis

Let: N= number of training samples. d= embedding dimension. K= semantic senses. V= graph nodes. E= graph edges. L= transformer layers. The contextual transformer encoder contributes approximately

$$O(Ld^2) \qquad (31)$$

The memory retrieval module contributes

$$O(Kd) \qquad (32)$$

Graph attention reasoning contributes

$$O(E) \qquad (33)$$

Therefore, the overall complexity becomes

$$O(Ld^2 + Kd + E) \qquad (34)$$

The overall computational formulation is polynomial in the relevant data, embedding, graph, and transformer dimensions. The analysis indicates that the framework can be applied to benchmark-scale semantic corpora such as SemCor and WiC, although practical scalability will also depend on graph size, memory-bank capacity, and transformer configuration.

4. RESULTS AND DISCUSSION

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The experiments were implemented in Python 3.10 or later using Hugging Face Transformers and PyTorch for transformer and deep-learning components, PyTorch Geometric and NetworkX for knowledge-graph processing, and NumPy, Pandas, and Scikit-learn for preprocessing and statistical analysis. Matplotlib and Seaborn were used for visualisation. The framework can be executed on systems with an Intel Core i7/i9 or AMD Ryzen 7/9 CPU, 16–32 GB RAM, and an NVIDIA RTX-series GPU with 8–12 GB memory. Ubuntu 22.04 LTS or Windows 11 with CUDA support can be used for experimentation.

4.1. Dataset Description

The SemCor [25] and WiC (Word-in-Context) [26] benchmark datasets are used to evaluate NeuroSymbolic-HomonymSenseNet for semantic sense classification and contextual meaning discrimination. SemCor is manually annotated using the Brown Corpus and WordNet sense labels, providing context-rich sentences with predefined semantic senses. WiC evaluates whether the same target word expresses the same meaning in two different sentence contexts. WordNet and Wikidata supply external lexical and entity-level relations for graph reasoning. The text is tokenised and encoded for transformer processing, and the datasets are divided into training, validation, and testing subsets using standard benchmark procedures. These resources support evaluation of contextual understanding, rare-sense preservation, semantic consistency, reasoning, and explainability.

Table 1. Overall Semantic Sense Classification Performance on SemCor.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Word2Vec	80.52	79.94	79.11	79.52
GloVe	82.17	81.64	80.93	81.28
BERT	89.74	89.28	88.92	89.10
RoBERTa	91.86	91.37	91.12	91.24
SenseBERT	93.71	93.26	92.95	93.10
NeuroSymbolic-HomonymSenseNet	**97.83**	**97.46**	**97.21**	**97.33**

Table 1 shows that NeuroSymbolic-HomonymSenseNet achieves the highest performance among the evaluated models on SemCor, with 97.83% accuracy, 97.46% precision, 97.21% recall, and 97.33% F1-score. Compared with the strongest listed baseline, SenseBERT, the proposed framework improves accuracy by 4.12 percentage points and F1-score by 4.23 percentage points. The improvement is consistent across all four measures, supporting the hypothesis that combining contextual learning with dynamic memory and structured reasoning can improve homonym sense discrimination.

Table 2. Contextual Understanding Performance on WiC Dataset.

Model	Accuracy (%)	MCC	Precision (%)	F1-Score (%)
Word2Vec	78.93	0.57	78.21	77.94
GloVe	80.76	0.61	80.15	79.83
BERT	88.84	0.77	88.42	88.15
RoBERTa	90.73	0.81	90.28	90.04
SenseBERT	92.64	0.85	92.18	91.97
NeuroSymbolic-HomonymSenseNet	**96.91**	**0.94**	**96.44**	**96.22**

Table 2 reports contextual meaning discrimination on WiC. NeuroSymbolic-HomonymSenseNet achieves the highest accuracy (96.91%), MCC (0.94), precision (96.44%), and F1-score (96.22%). Relative to SenseBERT, accuracy improves by 4.27 percentage points and MCC increases by 0.09. These results support the hypothesis that contextual representations benefit from complementary structured semantic evidence, although the results should be interpreted within the scope of the evaluated benchmarks.

Table 3. Rare-Sense and Explainability Evaluation.

Model	Rare-Sense Recall (%)	Rare-Sense F1 (%)	Explainability Score (%)
Word2Vec	62.34	63.11	12.52
GloVe	65.48	66.02	15.84
BERT	79.73	80.12	43.19
RoBERTa	82.47	82.93	48.74
SenseBERT	86.66	87.04	56.38
NeuroSymbolic-HomonymSenseNet	**95.18**	**95.42**	**91.75**

Table 3 evaluates rare-sense preservation and explainability. NeuroSymbolic-HomonymSenseNet achieves 95.18% rare-sense recall, 95.42% rare-sense F1-score, and a 91.75% explainability score. Relative to SenseBERT, rare-sense recall and F1-score improve by 8.52 and 8.38 percentage points, respectively, while explainability increases by 35.37 percentage points. These results directly address the identified research problem concerning low-frequency sense preservation and transparent semantic interpretation.

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Table 4. Knowledge Graph and Neuro-Symbolic Reasoning Analysis.

Model	Semantic Consistency (%)	Reasoning Accuracy (%)	Knowledge Utilization (%)
Word2Vec	68.74	65.83	0.00
GloVe	70.51	67.24	0.00
BERT	84.63	81.59	0.00
RoBERTa	87.82	84.66	0.00
SenseBERT	90.34	88.41	21.73
NeuroSymbolic-HomonymSenseNet	**98.11**	**97.28**	**94.83**

Table 4 evaluates knowledge-graph integration and neuro-symbolic reasoning. NeuroSymbolic-HomonymSenseNet records 98.11% semantic consistency, 97.28% reasoning accuracy, and 94.83% knowledge utilisation. Compared with SenseBERT, the corresponding improvements are 7.77, 8.87, and 73.10 percentage points. These results indicate that the explicit use of WordNet and Wikidata contributes measurable structured-knowledge utilisation beyond contextual representation alone.

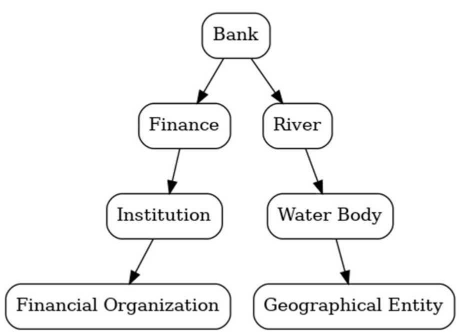

Figure 2. Semantic Knowledge Graph Reasoning Visualization.

Figure 2 illustrates semantic reasoning routes for the homonym "bank." The financial route connects concepts such as Finance, Institution, and Financial Organization, whereas the geographical route connects River, Water Body, and Geographical Entity. The example provides qualitative evidence of how structured semantic relations can support disambiguation and make the reasoning path more inspectable than a prediction based only on contextual similarity.

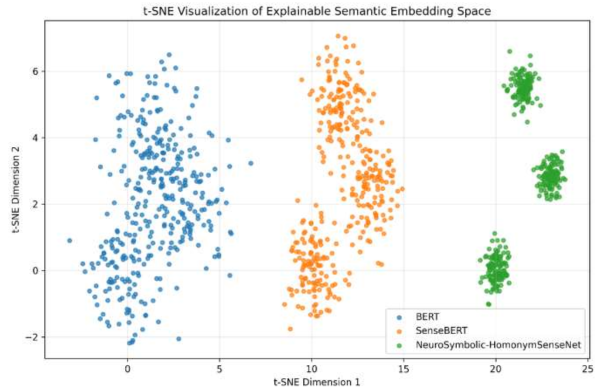

Figure 3. t-SNE Visualization of Explainable Semantic Embedding Space.

Figure 3 presents a t-SNE comparison of the semantic embedding spaces produced by BERT, SenseBERT, and NeuroSymbolic-HomonymSenseNet. The proposed framework shows more compact and separated clusters, whereas BERT exhibits greater overlap and SenseBERT shows improved but incomplete separation. The visualisation is consistent with the contrastive and graph-aware design, although t-SNE should be interpreted as qualitative evidence rather than a standalone quantitative measure of representation quality.

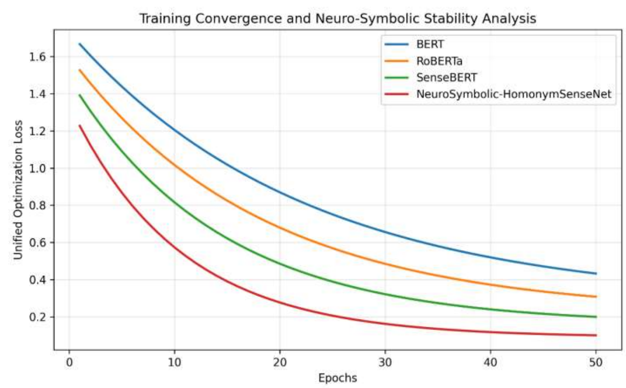

Figure 4. Training Convergence and Neuro-Symbolic Stability Analysis.

Figure 4 compares training convergence for BERT, RoBERTa, SenseBERT, and NeuroSymbolic-HomonymSenseNet. The proposed framework reaches a stable loss region earlier and exhibits fewer visible optimisation fluctuations. The result is consistent with the intended contribution of dynamic memory and neuro-symbolic consistency, but the convergence plot should be interpreted as supporting evidence rather than proof of general optimisation superiority.

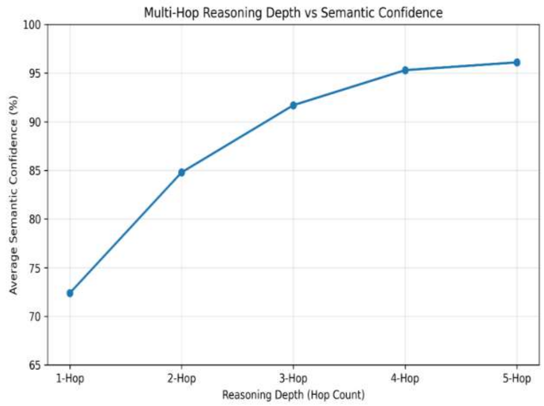

Figure 5. Multi-Hop Reasoning Depth vs Semantic Confidence.

Figure 5 shows semantic confidence as reasoning depth increases from one-hop to four-hop analysis. Confidence increases through four hops and then approaches saturation, suggesting diminishing additional semantic information beyond this depth in the evaluated setting. The trend provides qualitative evidence that multi-hop graph reasoning contributes to contextual disambiguation and confidence estimation.

4.5 Difference from Prior Work and Achievement of Objectives

The proposed framework differs from the reviewed approaches in the way it combines four objectives that are commonly treated separately: contextual representation, rare-sense preservation, structured semantic reasoning, and explainability. The quantitative results indicate that these objectives are reflected in measurable gains. On SemCor, the proposed model exceeds SenseBERT by 4.12 percentage points in accuracy and 4.23 percentage points in F1-score; on WiC, the accuracy gain is 4.27 percentage points. For rare-sense evaluation, recall and F1-score improve over SenseBERT by 8.52 and 8.38 percentage points, respectively. Knowledge-graph semantic consistency and reasoning accuracy reach 98.11% and 97.28%, while knowledge utilisation reaches 94.83%. These results indicate that the framework achieves the stated objectives more comprehensively than the listed contextual baselines. However, the principal limitation of the comparison is that the evaluation is restricted to SemCor and WiC and therefore does not establish domain-independent superiority.

4.6 Limitations and Scope of Validity

The study has several limitations. First, evaluation is restricted to the SemCor and WiC benchmark datasets, so the findings may not generalise to multilingual, domain-specific, or substantially different text distributions. Second, the quality and coverage of the external WordNet and Wikidata resources can influence graph reasoning. Third, the reported explainability measures and qualitative reasoning paths demonstrate interpretability within the proposed framework but do not constitute a human-grounded causal explanation. Finally, the modular architecture introduces additional memory and computational requirements compared with a standalone contextual encoder. These limitations define the current scope of the conclusions and motivate broader cross-domain and multilingual validation.

5. CONCLUSION AND FUTURE SCOPE

The central problem addressed in this study was the joint need for accurate homonym disambiguation, preservation of rare semantic senses, and interpretable semantic reasoning. The proposed NeuroSymbolic-HomonymSenseNet responds to this problem by integrating contextual encoding, Dynamic Sense Memory Bank, WordNet–Wikidata knowledge-graph reasoning, GARN, NS-SIE, and Explainable Contrastive Multi-Sense Optimisation within one framework. The hypothesis was that combining these complementary mechanisms would improve semantic discrimination and interpretability compared with representation methods that rely primarily on contextual or distributional information.

The experimental evidence supports this hypothesis. On SemCor, the framework achieves 97.83% accuracy and 97.33% F1-score, improving over SenseBERT by 4.12 and 4.23 percentage points, respectively. On WiC, it achieves 96.91% accuracy and an MCC of 0.94, with a 4.27-point accuracy improvement over SenseBERT. Rare-sense recall and F1-score reach 95.18% and 95.42%, while explainability reaches 91.75%. Knowledge-graph analysis further reports 98.11% semantic consistency, 97.28% reasoning accuracy, and 94.83% knowledge utilisation. These findings provide direct evidence that persistent sense memory and explicit symbolic knowledge can complement contextual neural representations. Nevertheless, the evaluation is limited to SemCor and WiC, and the reported results should not be interpreted as evidence of universal superiority across languages, domains, or unseen corpora. Future work should therefore examine multilingual and cross-domain settings, dynamically updated knowledge graphs, retrieval-augmented generation, larger language models, and federated neuro-symbolic learning.

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