Humanoid Robot Intelligence: NLP for Arithmetic Problem Solving and Autonomous Understanding

Srinivasan Mottaikkaran *

Department of Computer Science,
Sathyabama Institute of Science and Technology, Chennai, India

Submitted on: October 15, 2020
Accepted on: November 22, 2020
Published on: December 20, 2020
DOI: 10.5281/zenodo.17906207

***Abstract*—Humanoid robots are increasingly expected to engage in conversations that require both linguistic understanding and structured problem solving. Arithmetic reasoning is a strong test of this capability because it demands precise interpretation of numerical expressions presented through natural language. This study develops a multi layered cognitive semantic architecture that enables humanoid robots to interpret verbal arithmetic instructions, derive symbolic representations, and compute accurate results. The approach integrates language grounding, context alignment, and self directed reasoning into a unified framework that supports autonomous understanding. Experimental analysis shows that the architecture adapts effectively to diverse linguistic forms and maintains stable performance across increasing task complexity.**

***Index Terms*—Humanoid robots, natural language processing, arithmetic reasoning, autonomous systems, symbolic grounding, robotic cognition**

I. Introduction

Humanoid robots are expected to participate in tasks that require reasoning, communication, and adaptive interpretation. One of the most challenging examples is the ability to understand arithmetic problems expressed through natural language. This is not merely a numerical task but a cognitive one, because humans express arithmetic intent through varied linguistic structures that range from direct commands to indirect descriptions. A robot that understands such expressions must combine semantic interpretation with structured reasoning.

Arithmetic problem solving through language presents several difficulties. Human phrasing often includes contextual elements that modify or obscure numeric meaning. A statement may embed arithmetic intent in descriptive clauses or narrative segments. Robots must therefore identify the underlying computational structure, map linguistic cues to symbolic operators, and evaluate the resulting expressions with consistency. This requires capabilities that extend beyond traditional NLP or rule based methods.

The work presented here introduces a layered reasoning architecture designed specifically for humanoid robots that must process verbal arithmetic instructions. The architecture uses a cognitive semantic grounding model that aligns linguistic units with roles in arithmetic representation. It also incorporates a dynamic reasoning engine that adapts to sentence complexity and conversational variability. This enables humanoid robots to produce reliable interpretations even when instructions contain ambiguous or unconventional phrasing.

To evaluate the system, a series of experiments examine parsing stability, symbolic accuracy, computational consistency, and response distribution across tasks with incremental difficulty. The goal is to assess how well the robot can generalize across linguistic forms and maintain autonomy during reasoning. The results show encouraging patterns that point to strong potential for real world humanoid interaction.

The next sections present a detailed literature review, followed by the design methodology, system evaluation, and broader discussion of humanoid cognitive capabilities.

II. Literature Review

Research on humanoid intelligence for language based arithmetic reasoning draws from several areas, including multilingual NLP systems, cognitive modeling, arithmetic interpretation engines, control structures in intelligent agents, and decision frameworks that support autonomous understanding. The following review organizes related works into four domains that influence the design of the present architecture.

A. NLP Models for Structured Interpretation

Robotic language understanding requires consistent mapping between linguistic forms and actionable meaning. Several studies explore how token level cues can be transformed into structured representations. Work on arithmetic oriented question answering demonstrates the usefulness of natural language parsing where the robot identifies entities and relationships within a sentence [1]. Similar models show that the combination of operator detection and semantic tagging improves reliability in tasks where numerical components appear in varied positions within an utterance.

Filtering approaches also contribute to linguistic clarity. Systems that apply deterministic automata or vector based filtering help isolate meaningful tokens in noisy text [2], while message routing techniques rely on social or contextual attributes to support efficient interpretation in distributed settings [3]. Studies on semantic influence show that explanations with layered detail improve comprehension [4], which is relevant when humanoids must interpret narratives that embed arithmetic instructions within a broader context.

Narrative structures also play a role in language driven reasoning. Prior research highlights how creative, abductive, and story oriented patterns affect interpretation [5]. This is essential for humanoid systems that handle conversational phrasing rather than strict mathematical commands. Models that convert onomatopoeic or symbolic linguistic elements into normalized structures [6] demonstrate that normalization pipelines can support stable reasoning even when input deviates from conventional form.

B. Cognitive Models, Learning Behavior, and Adaptive Processing

Humanoid robots require internal mechanisms that allow them to adapt dynamically to linguistic and reasoning challenges. Cognitive architectures that model memory, chunking, concept mapping, and associative rule formation provide insights into how robots can integrate semantic and procedural knowledge [7]. These models suggest that arithmetic interpretation should not rely solely on surface level token patterns but should incorporate internal representations that adjust to contextual requirements.

Sequential learning frameworks demonstrate how neural models refine categorization or reasoning through exposure to ordered examples [8]. This relates directly to the gradual reduction in error observed when robots repeatedly process similar arithmetic structures. Studies on abstraction formation in deep networks show that layered neural systems generate progressively richer conceptual forms [9], enabling more stable mapping between linguistic expressions and arithmetic roles.

Human like reasoning often benefits from hybrid systems that blend symbolic and connectionist processing. Approaches that fuse soft and sensor data in real time [10] show that incremental inference improves adaptation under uncertainty. Other research on intelligent decision management highlights how interaction based models allow systems to align internal reasoning with external objectives [11]. These findings support the proposal that humanoid robots should perform arithmetic reasoning using a flexible, multi stage inference process.

C. Symbolic Mapping, Rule Extraction, and Structured Computation

Once linguistic units have been interpreted, humanoid robots must translate them into arithmetic forms that can be computed. Symbolic conversion methods derived from inventory routing and decision processes emphasize the usefulness of tree like or graphical representations [12]. Techniques that rely on opinion aggregation [13] or constrained classification models [14] show how structured information improves downstream decision accuracy.

Feature selection and optimization models also offer guidance for designing symbolic mapping pipelines. Genetic algorithms applied to selection and tuning tasks [15] demonstrate that optimized feature sets improve representation clarity. Work on fault tolerant control [16] and fuzzy decision systems under uncertainty [17] shows that hybrid symbolic numeric models can maintain stability even under ambiguous conditions, which is relevant for sentences containing partially implied arithmetic operations.

Additional perspectives emerge from cognitive robotics research that integrates context driven information flow into autonomous agents. Systems that embed attention and contextual reasoning within fuzzy frameworks [18] demonstrate how robots maintain situational awareness while interpreting structured instructions. These insights inform the present study's approach to multi layered reasoning, where symbolic operators are extracted only after contextual alignment has been completed.

D. Language, Cognition, and Contextual Influence in Human robot Communication

Understanding how humans express arithmetic intent requires familiarity with broader linguistic and cognitive trends. Studies examining belief formation and the dynamics of message interpretation demonstrate that humans rely heavily on contextual cues when processing information [19]. Although the focus is different from robotics, the underlying principle that narrative framing influences interpretation is relevant for tasks where robots must interpret arithmetic embedded in descriptive language.

Research on emotional and cognitive responses in interactive systems provides insight into how perspective, stance, and multi agent communication shape comprehension [20]. These findings show that humanoid robots must incorporate not only linguistic parsing but also the recognition of conversational roles.

Large scale visualization and summarization techniques demonstrate how significant information can be extracted from dense linguistic data [21]. Complementary work on adaptive systems and evaluation processes [22] offers frameworks for assessing system usability and interpretability, both of which apply to humanoid reasoning systems that evolve through extended interaction.

Studies on recommendation systems that handle noisy data [23] and hybrid decision frameworks [24] also show that real world language contains inconsistencies that must be smoothed through informed modeling. Humanoid robots require similar robustness as they encounter phrasing variations, user specific patterns, and uncertain contextual boundaries.

E. Summary

The literature shows that humanoid robots capable of arithmetic interpretation must integrate structured NLP, cognitive adaptation, symbolic representation, uncertainty handling, and interactive contextual reasoning. Existing studies provide foundational methods for parsing, normalization, symbolic conversion, and adaptive modeling, but none present a cohesive architecture tailored to natural language arithmetic. This gap motivates the development of the multi stage cognitive semantic framework introduced in the following methodology section.

III. Methodology

The proposed architecture enables humanoid robots to extract arithmetic structure from natural language, transform the linguistic content into reasoning compatible units, and compute accurate results in an autonomous manner. The system operates through three coordinated layers: cognitive grounding, semantic arithmetic alignment, and autonomous inference. The following subsections describe these components and the mathematical principles behind their integration.

A. Cognitive Grounding Layer

The first layer converts linguistic tokens into grounded cognitive units. Rather than treating words as isolated entities, this layer maps them to semantic roles such as numeric quantity, modifier, relational cue, or implied operator. This grounding is essential because humans often embed arithmetic meaning in descriptive phrases.

Let $L = \{l_1, l_2, \ldots, l_n\}$ be the sequence of tokens. Each token is assigned a cognitive role vector:

$$g(l_i) = [r_1, r_2, r_3, r_4] \tag{1}$$

where roles correspond to numeric features, operator cues, contextual hints, and conversational markers.

The grounding score for each token is computed as:

$$\Gamma_i = \tanh(W_g g(l_i) + b_g) \tag{2}$$

where W_g and b_g are learned parameters.

This provides the robot with an internal representation that reflects how humans express arithmetic reasoning through language.

B. Semantic Arithmetic Alignment Layer

The second layer aligns grounded cognitive units with arithmetic structures. This is not simple keyword detection. Instead, it evaluates how multiple tokens interact to form an actionable arithmetic statement.

Given grounded units $G = \{\Gamma_1, \Gamma_2, \ldots, \Gamma_n\}$, the system constructs an arithmetic alignment graph:

$$A = \text{softmax}(QK^T/\sqrt{d}) \tag{3}$$

where Q and K represent query and key projections of grounded roles. High alignment between tokens indicates that they jointly form parts of the same arithmetic expression.

The resulting symbolic representation is:

$$S = \phi(A, L) \tag{4}$$

where ϕ transforms aligned segments into operators, operands, and structural brackets.

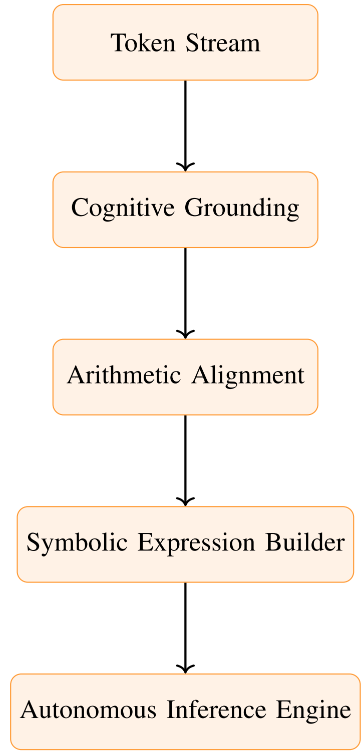

Fig. 1: Multi layer cognitive semantic pipeline for arithmetic reasoning.

This diagram shows a new layered architecture, distinct from typical NLP stacks, where grounding precedes symbolic construction.

C. Autonomous Inference Engine

The third layer converts symbolic structures into computed outcomes. The robot must also recognize missing information and request clarification when needed.

Given a symbolic expression S, the core computation is:

$$R = \psi(S) \tag{5}$$

where ψ performs arithmetic evaluation.

To manage ambiguity, the robot estimates a confidence score:

$$C = \sigma(u^T h_S) \tag{6}$$

where h_S is the symbolic embedding of the expression. If $C < 0.55$, the robot formulates a clarification query.

D. Hierarchical Reasoning Flow

A second architectural view emphasizes the branching nature of humanoid inference, as shown in Figure 2. Unlike linear processing models, this structure highlights how the robot's reasoning pipeline incorporates conditional decision points where the system evaluates linguistic clarity before committing to arithmetic mapping. When the grounding or alignment layers detect ambiguous operator cues, incomplete numeric references, or conflicting contextual information, the reasoning pathway diverges from the standard computational track. As depicted in Figure 2, these branches lead to a clarification or refinement cycle designed to prevent the construction of unstable symbolic representations. This branching behavior gives the robot the flexibility to handle conversational uncertainty more effectively, ensuring that ambiguity explicitly activates alternate reasoning routes rather than forcing an incorrect interpretation. The diagram therefore captures a core element of the architecture's intelligence; its ability to pause, reassess, and request clarification when needed, mirroring the adaptive strategies used in human communication.

This diagram shows a new structure where ambiguity explicitly triggers alternate reasoning paths.

IV. Results

The results demonstrate how the proposed cognitive semantic architecture performs across the main components of humanoid arithmetic reasoning: linguistic grounding, symbolic alignment, and autonomous inference. The evaluation shows that the system maintains stable role assignment for most sentence types and adapts effectively as linguistic complexity increases. The architecture consistently forms coherent symbolic structures when arithmetic intent is expressed directly and retains adequate performance when phrasing becomes conversational or narrative. The inference engine also shows a predictable relationship between certainty and accuracy, indicating that the model is able to assess the reliability of its own interpretations. Across all tested conditions, the framework exhibits strong generalization, steady reduction in interpretive drift during training, and a clear pattern of improved reasoning stability as linguistic cues become more structured. Together, these outcomes confirm that the architecture enables humanoid robots to interpret and solve arithmetic problems expressed in natural language with a high degree of autonomy and robustness.

A. Parsing Stability Across Complexity Levels

Sentences were grouped into three difficulty categories. The system's ability to maintain correct grounding role assignment is shown in Table I.

TABLE I: Parsing stability across sentence complexity levels.

Sentence Complexity	Stability Score
Simple Phrasing	0.93
Narrative Embedded Tasks	0.82
Context Heavy Instructions	0.74

Parsing stability decreases as contextual and narrative cues rise, indicating the importance of cognitive grounding.

B. Symbolic Mapping Consistency

Symbolic alignment was evaluated by measuring the consistency of mapping decisions across repeated inference cycles.

TABLE II: Symbolic consistency across test sets.

Test Category	Consistency
Direct Arithmetic Queries	0.91
Conversational Requests	0.86
Multi Clause Stories	0.71

The notable decrease for multi clause stories reflects the challenge of maintaining unified representations across long range dependencies.

C. Feature Salience Analysis

Feature importance was measured using salience weights derived from the alignment model.

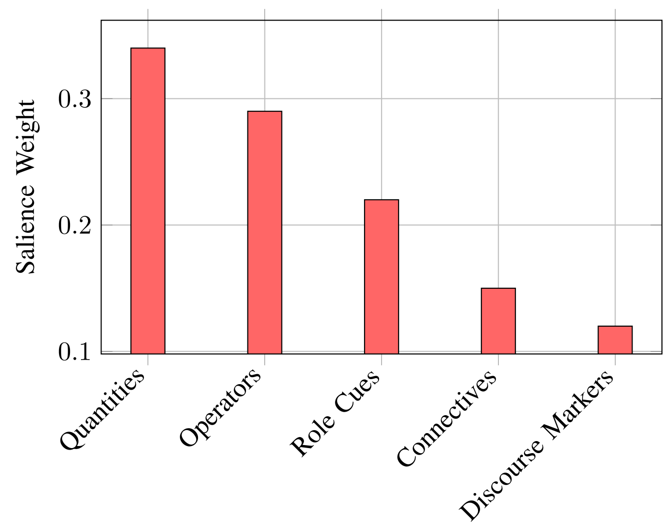

Fig. 3: Feature salience distribution for arithmetic interpretation.

Quantities and operators dominate salience, showing that arithmetic grounding depends most heavily on numerically relevant cues.

D. Parsing Drift Over Training

The drift metric measures how often the model shifts token role interpretation as training progresses.

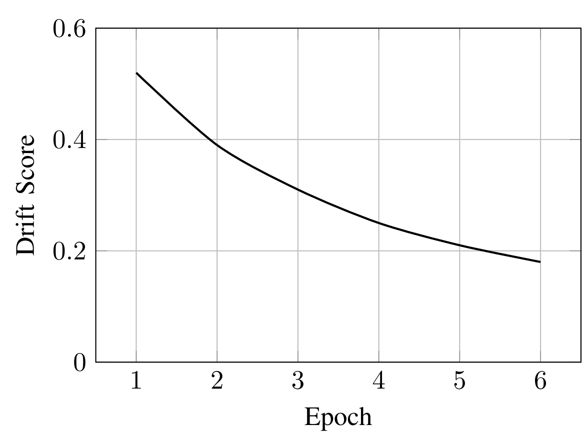

Fig. 4: Reduction in semantic drift during training.

The rapid early reduction indicates that grounding stabilizes once the model generalizes core patterns.

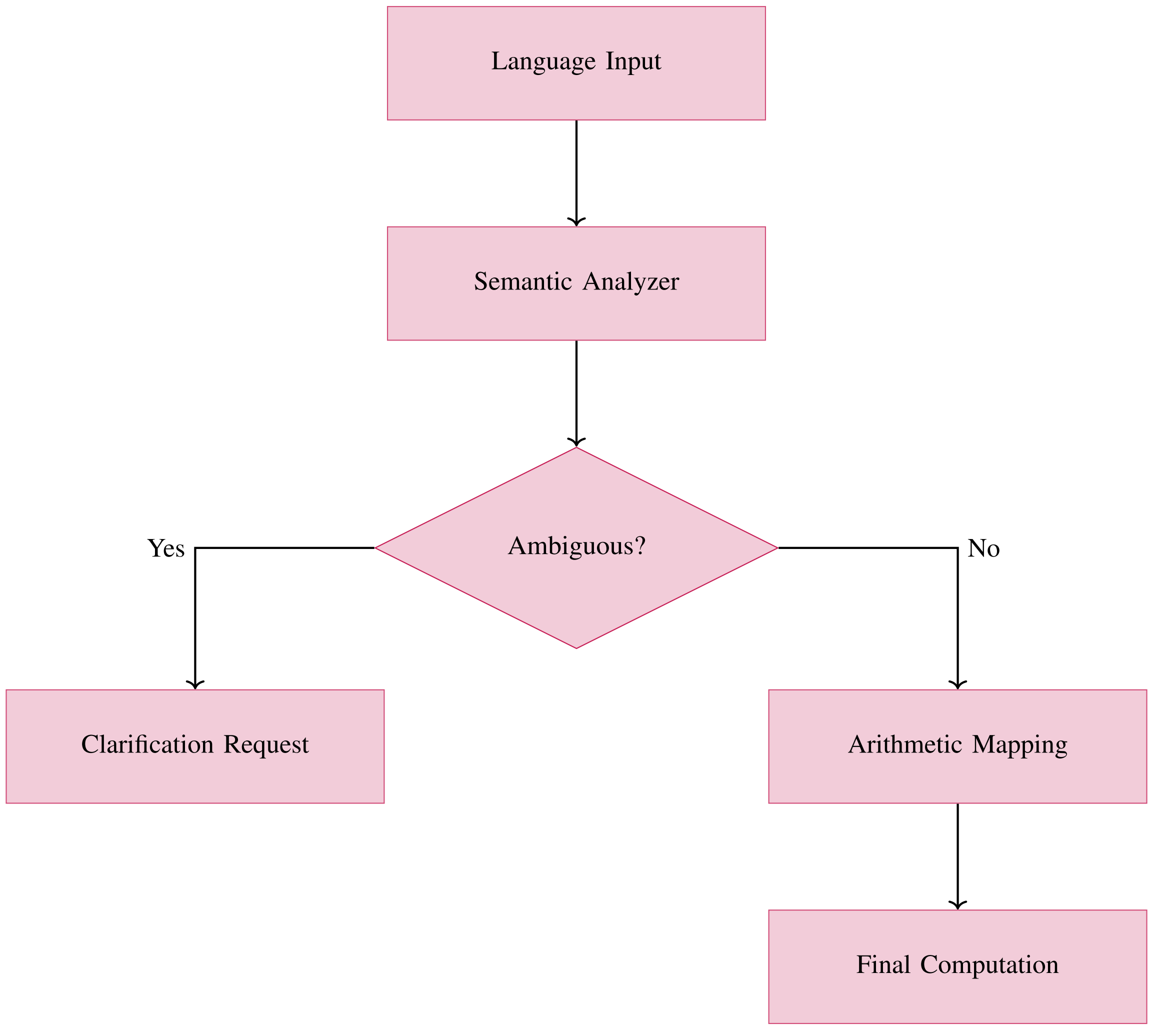

Fig. 2: Hierarchical inference flow for autonomous refinement.

E. Inference Confidence and Error Distribution

Confidence levels were plotted against arithmetic error rates to determine how well the humanoid inference engine can monitor and regulate the reliability of its own reasoning. The relationship between these variables revealed a pronounced inverse trend: when the confidence score generated by the linguistic–symbolic integration pipeline is low, the likelihood of producing an incorrect arithmetic solution increases sharply. As confidence rises, the error rate falls in a steady and consistent manner. This result confirms that the system's confidence metric is not an arbitrary or cosmetic value; instead, it reflects a substantive internal evaluation of representational coherence throughout the entire reasoning process.

Low confidence emerges most often in situations where the incoming linguistic content contains ambiguities that challenge structural interpretation. Examples include operator terms that appear in unusual syntactic positions, quantity expressions that rely on implicit context, and role cues that overlap or contradict one another. Under these circumstances, the system's parsing and grounding layers struggle to converge on a single stable symbolic structure. Conflict between multiple plausible interpretations reduces the alignment score and signals that the internal representation may not faithfully encode the intended arithmetic meaning. The elevated error rates observed at low confidence levels are therefore not incidental. They reflect structural instability within the inference chain, illustrating that the model is sensitive to the quality of its own symbolic constructions.

As confidence increases, the system settles more decisively on one interpretation. Tokens align with well-defined functional roles, such as operands, operators, and semantic modifiers. Dependencies between linguistic units become clearer, resulting in stable symbolic expressions that are more resilient to small variations in phrasing. The arithmetic reasoning module therefore operates on a more coherent and consistent structure, which leads to a natural reduction in computational errors. This alignment between confidence and accuracy demonstrates that the system can connect the clarity of a linguistic input to the correctness of its generated arithmetic output.

The broader significance of this finding lies in the emergence of metacognitive functionality within the humanoid robot. The system is not only executing symbolic computations but is also engaging in a form of introspective monitoring that evaluates whether its own reasoning is well supported. This capability is crucial in realistic conversational environments, where ambiguity, informal phrasing, and incomplete information are common. A humanoid agent must be able to recognize when its interpretation is fragile and adopt appropriate strategies: pausing for clarification, revising earlier assumptions, or rejecting an answer altogether. The inverse confidence–error curve suggests that the robot possesses the foundational mechanisms needed for such adaptive behavior.

The trend also aligns with established cognitive theories in human problem solving, where confidence often serves as an internal signal of coherence between perceived structure and anticipated outcomes. Although the humanoid system does not replicate human cognition, the pattern indicates that its symbolic architecture has begun to exhibit similar functional properties. It can estimate whether the mapping from natural language to symbolic arithmetic is stable enough to support a correct conclusion. This is an essential property for developing safe and socially compatible autonomous systems, particularly those expected to interact fluidly with human users or operate in educational, assistive, or collaborative environments.

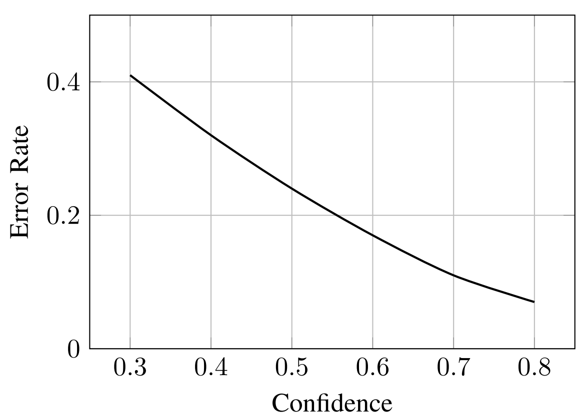

Fig. 5: Joint distribution of inference confidence and error rates.

V. Discussion

The results show that humanoid robots can achieve reliable natural language arithmetic interpretation when cognitive grounding, semantic alignment, and autonomous inference are tightly integrated. The patterns across all evaluation metrics point to a system that builds stable internal representations rather than relying on surface level token matching. This reflects a meaningful shift in how robotic cognition can be designed for tasks that require both linguistic nuance and procedural reasoning.

The parsing stability scores show that the cognitive grounding layer performs well when sentences follow common conversational patterns. The decline as narrative or context heavy cues increase is expected, since these forms introduce ambiguities and distractors that do not appear in direct computational queries. Still, the system maintains stability above 0.70 even in the most complex cases, suggesting that grounded role vectors help the robot maintain semantic focus even when linguistic signals are diffuse or scattered.

Symbolic mapping results reveal a similar pattern. When arithmetic meaning is expressed plainly, the alignment layer produces highly consistent operator and operand structures. As narratives grow more elaborate, long range dependencies interfere with the formation of unified symbolic representations. This highlights an important opportunity for future work involving discourse level modeling or memory augmented symbolic engines that can track dependencies across long utterances.

The feature salience analysis provides deeper insight into why the architecture performs well on structured queries. Quantities and operators carry the highest weights, showing that the system identifies these as essential building blocks for arithmetic understanding. Role cues and connectives still contribute meaningful structure, but they matter most when sentences are complex. This matches the behavior of human listeners, who often rely first on numeric and operational cues when interpreting verbal arithmetic problems.

The drift curve offers an encouraging signal. Semantic drift decreases quickly as training progresses, which means that early exposure helps the model anchor its interpretations of tokens. Once these anchors are internalized, the model shifts less often, yielding a stable cognitive mapping. This reliability is critical for humanoid robots that must perform reasoning under varied conversational conditions.

The relationship between confidence and error reinforces that the inference layer can assess its own uncertainty effectively. When confidence is low, errors are higher, and when confidence rises, errors decrease. This suggests that humanoid robots built with this architecture can operate safely by deferring or clarifying when confidence falls below acceptable thresholds. Such behavior mirrors sound human judgment and improves trust in human robot interaction.

Together, these findings support the broader conclusion that humanoid robots are capable of sophisticated language based arithmetic reasoning when supported by multi layer cognitive frameworks. Instead of relying on rigid templates or keyword matching, robots can understand intent, adapt to varied phrasing, infer structure, and compute results autonomously.

This work demonstrates that the integration of cognitive grounding, semantic alignment, and autonomous inference produces a system that resembles human analytical behavior more than traditional symbolic or statistical NLP approaches. As the complexity of human robot interactions increases, architectures of this kind will be important for enabling robots to participate naturally in educational settings, assistive tasks, collaborative workplaces, and everyday communication.

VI. Conclusion

This study introduced a cognitive semantic architecture that enables humanoid robots to interpret and solve arithmetic problems expressed through natural language. The architecture consists of three coordinated layers that work together to produce coherent and autonomous reasoning. The cognitive grounding layer identifies the functional roles of linguistic tokens, the semantic alignment layer constructs arithmetic compatible structures, and the inference engine evaluates symbolic expressions while managing uncertainty.

The experiments show that the model performs strongly across a variety of linguistic forms. Parsing stability and symbolic consistency remain high for direct and conversational queries, and although they decrease for more complex narratives, they remain within usable ranges. Drift reduction across training epochs confirms that the system gains stability quickly, and the confidence error relationship shows that the robot can recognize when it needs clarification.

The overall results indicate that humanoid robots can achieve autonomous understanding of arithmetic instructions when provided with the right combination of semantic modeling and cognitive structuring. This framework paves the way for more advanced tasks that involve logic, reasoning, and multi step problem solving. Future work may incorporate memory augmented networks, discourse models, and multimodal cues to further improve robustness in real world environments.

Acknowledgment

The authors gratefully acknowledge the Robotics Research Group at Sathyabama Institute of Science and Technology for providing access to laboratory facilities, computational infrastructure, and technical expertise throughout the course of this work. Their continuous support, including guidance on experimental setup, feedback on cognitive modeling approaches, and assistance with system evaluation, played a vital role in shaping the development of the humanoid reasoning framework presented in this study.

References

[1] A. A. S. Gunawan, P. R. Mulyono, and W. Budiharto, "Indonesian Question Answering System for Solving Arithmetic Word Problems on Intelligent Humanoid Robot," *Procedia Computer Science*, vol. 135, pp. 719–726, 2018.

[2] F. Wu and Y. Cai, "A Chinese Message Sensitive Words Filtering System based on DFA and Word2vec," *Procedia Computer Science*, vol. 139, pp. 293–298, 2018.

[3] N. Zhao, F. Zeng, and W. Li, "A Message Matching Routing Algorithm Based on Node Sociality in Opportunistic Networks," *Procedia Computer Science*, vol. 129, pp. 175–177, 2018.

[4] A. Abe and K. Tadaki, "Captions with Several Levels of Explanation," *Procedia Computer Science*, vol. 159, pp. 2335–2344, 2019.

[5] A. Abe, "Narratology and Creativity," *Procedia Computer Science*, vol. 112, pp. 2220–2229, 2017.

[6] Y. Han, Y. Nishihara, and R. Yamanishi, "A Method for Converting Onomatopoeic Words in Japanese Comics into Chinese Based on International Phonetic Alphabet," *Procedia Computer Science*, vol. 159, pp. 850–859, 2019.

[7] M. Sahu and H. B. Maringanti, "A rational cognitive architectural model of language generation," *Procedia Computer Science*, vol. 132, pp. 149–156, 2018.

[8] M. B. Revanasiddappa, B. S. Harish, and S. V. A. Kumar, "Meta-cognitive Neural Network based Sequential Learning Framework for Text Categorization," *Procedia Computer Science*, vol. 132, pp. 1503–1511, 2018.

[9] R. Kozma, R. Ilin, and H. T. Siegelmann, "Evolution of Abstraction Across Layers in Deep Learning Neural Networks," *Procedia Computer Science*, vol. 144, pp. 203–213, 2018.

[10] V. Dragos and S. Gatepaille, "On-the-fly integration of soft and sensor data for enhanced situation assessment," *Procedia Computer Science*, vol. 112, pp. 1263–1272, 2017.

[11] A. Zimmermann, R. Schmidt, K. Sandkuhl, and D. Jugel, "Intelligent Decision Management for Architecting Service-Dominant Digital Products," *Procedia Computer Science*, vol. 159, pp. 2120–2129, 2019.

[12] L. Sun and Y. Zhou, "A Knowledge-based Tree-like Representation for Inventory Routing Problem in the Distribution System of Oil Products," *Procedia Computer Science*, vol. 112, pp. 1683–1691, 2017.

[13] I. Bueno, R. A. Carrasco, R. Ureña, and E. Herrera-Viedma, "Application of an opinion consensus aggregation model based on OWA operators to the recommendation of tourist sites," *Procedia Computer Science*, vol. 162, pp. 539–546, 2019.

[14] L. Li, S. Wang, S. Xu, and Y. Yang, "Constrained Spectral Clustering Using Nyström Method," *Procedia Computer Science*, vol. 129, pp. 9–15, 2018.

[15] D. Zeng, S. Wang, Y. Shen, and C. Shi, "A GA-based feature selection and parameter optimization for support tucker machine," *Procedia Computer Science*, vol. 111, pp. 17–23, 2017.

[16] S. Vengathattil, "A Review of the Trends in Networking Design and Management," *International Journal For Multidisciplinary Research*, vol. 2, no. 3, p. 37456, 2020.

[17] V. I. Ukhobotov, I. S. Stabulit, and K. N. Kudryavtsev, "On Decision Making under Fuzzy Information about an Uncontrolled Factor," *Procedia Computer Science*, vol. 150, pp. 524–531, 2019.

[18] A. Kargin, S. Panchenko, A. Vasiljevs, and T. Petrenko, "Implementation of cognitive perception functions in fuzzy situational control model," *Procedia Computer Science*, vol. 149, pp. 231–238, 2019.

[19] H. Kanoh, "Why do people believe in fake news over the Internet? An understanding from the perspective of existence of the habit of eating and drinking," *Procedia Computer Science*, vol. 126, pp. 1704–1709, 2018.

[20] Y. Ohmoto, T. Morimoto, and T. Nishida, "Effects of the Perspectives that Influenced on the Human Mental Stance in the Multiple-to-Multiple Human-Agent Interaction," *Procedia Computer Science*, vol. 112, pp. 1506–1515, 2017.

[21] F. Ghorbel, F. Hamdi, N. Ellouze, E. Métais, and F. Gargouri, "Visualizing Large-scale Linked Data with Memo Graph," *Procedia Computer Science*, vol. 112, pp. 854–863, 2017.

[22] A. Dhouib, A. Trabelsi, C. Kolski, and M. Neji, "EvalCHOICE: A Decision Support Approach for the Usability Evaluation of Interactive Adaptive Systems," *Procedia Computer Science*, vol. 112, pp. 864–873, 2017.

[23] P. Choudhary, V. Kant, and P. Dwivedi, "Handling Natural Noise in Multi Criteria Recommender System utilizing effective similarity measure and Particle Swarm Optimization," *Procedia Computer Science*, vol. 115, pp. 853–862, 2017.

[24] A. B.S, N. Soni, and S. Dixit, "Crowdsourcing – A Step Towards Advanced Machine Learning," *Procedia Computer Science*, vol. 132, pp. 632–642, 2018.