Neuro-Symbolic AI: Bridging Learning and Reasoning for Next-Generation Intelligent Systems

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SUBMITTED BY:

DHWANI SINGH (2K21/CO/159)

DRUTI CHOUDHURY (2K21/CO/164)

UNDER THE SUPERVISION OF

PROF. VINOD KUMAR

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Bawana Road, Delhi-110042

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DEPT. OF COMPUTER SCIENCE AND ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Bawana Road, Delhi-110042

CANDIDATE'S DECLARATION

We, Dhwani Singh (2K21/CO/159) & Druti Choudhury (2K21/CO/164) students of B.Tech (Computer Engineering), hereby declare that the Project Dissertation titled — "Neuro-Symbolic AI: Bridging Learning and Reasoning for Next-Generation Intelligent Systems" which is submitted by us to the Department of Computer Science and Engineering, DTU, Delhi in fulfilment of the requirement for awarding of the Bachelor of Technology degree, is not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma, Fellowship or other similar title or recognition.

Place: New Delhi	Dhwani Singh	Druti Choudhury
Date: 22/05/2025	2K21/CO/159	2K21/CO/164

DEPT. OF COMPUTER SCIENCE AND ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Bawana Road, Delhi-110042

CERTIFICATE

I hereby certify that the Project titled " Neuro-Symbolic AI: Bridging Learning and Reasoning for Next-Generation Intelligent Systems" which is submitted by Dhwani Singh (2K21/CO/159) & Druti Choudhury (2K21/CO/164) for fulfilment of the requirements for awarding of the degree of Bachelor of Technology (B. Tech) is a record of the project work carried out by the students under my guidance & supervision. To the best of my knowledge, this work has not been submitted in any part or fulfilment for any Degree or Diploma to this University or elsewhere.

Place: New Delhi
Date: 22/05/2025

Prof. Vinod Kumar
(SUPERVISOR)
Professor
Department of Computer Science and Engineering
Delhi Technological University

ABSTRACT

Neuro-Symbolic AI (NSAI) is an emerging field that seeks to combine the structured, rule-based reasoning of symbolic systems with the adaptive, data-driven learning capabilities of neural networks. This hybrid approach addresses the limitations of purely symbolic or purely neural models, creating AI systems that can reason about the world with the precision of logic while adapting to new data like neural models. By integrating these complementary paradigms, NSAI aims to develop more interpretable, scalable, and robust AI systems capable of tackling complex real-world problems.

This literature review provides a comprehensive overview of the key components of NSAI, including foundational concepts like representation spaces, knowledge representation, and logical reasoning. It examines a range of neuro-symbolic architectures, from Logic Tensor Networks and Neuro-Symbolic Concept Learners to more advanced cognitive systems that incorporate both neural learning and symbolic logic. The project also explores practical applications across diverse fields such as healthcare, geoscience, military systems, and patient monitoring, highlighting the transformative potential of NSAI. Additionally, it discusses the major challenges facing the field, including scalability, interpretability, knowledge acquisition, and ethical considerations, emphasizing the ongoing research needed to overcome these obstacles.

Furthermore, the review covers essential datasets and bench- marks like CLEVR, GQA, and NS-VQA, which play a critical role in evaluating the performance of neuro-symbolic systems. It also outlines promising future directions, including the development of unified representations, scalable learning algorithms, enhanced

explainability, and ethically sound designs, which are essential for achieving human-level general intelligence.

Overall, this project aims to provide researchers, practitioners, and industry leaders with a comprehensive understanding of the current landscape and future prospects of Neuro-Symbolic AI, offering a roadmap for the continued evolution of this critical field.

ACKNOWLEDGEMENT

The successful completion of any task is incomplete and meaningless without giving any due credit to the people who made it possible without which the project would not have been successful and would have existed in theory.

First and foremost, we are grateful to Dr. Manoj Kumar, HOD, Department of Computer Science and Engineering, Delhi Technological University, and all other faculty members of our department for their constant guidance and support, constant motivation and sincere support and gratitude for this project work. We owe a lot of thanks to our supervisor, Prof. Vinod Kumar, Professor, Department of Computer Science and Engineering, Delhi Technological University for igniting and constantly motivating us and guiding us in the idea of a creatively and amazingly performed Major Project in undertaking this endeavour and challenge also for being there whenever we needed his guidance or assistance.

We would also like to take this moment to show our thanks and gratitude to one and all, who indirectly or directly have given us their hand in this challenging task. We feel happy, joyful and content in expressing our vote of thanks to all those who have helped us and guided us in presenting this project work for our Major project. Last, but never least, we thank our well-wishers and parents for always being with us, in every sense and constantly supporting us in every possible sense whenever possible.

DHWANI SINGH
(2K21/CO/159)

DRUTI CHOUDHURY
(2K21/CO/164)

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LIST OF SYMBOLS, ABBREVIATIONS AND NOMENCLATURE

Abbreviation	Full Form
NSAI	Neuro-Symbolic Artificial Intelligence
AI	Artificial Intelligence
NN	Neural Network
DL	Deep Learning
ML	Machine Learning
RL	Reinforcement Learning
VQA	Visual Question Answering
NS-VQA	Neuro-Symbolic Visual Question Answering
LTN	Logic Tensor Network
GNN	Graph Neural Network
FOL	First-Order Logic
SRL	Statistical Relational Learning
CLEVR	Compositional Language and Elementary Visual Reasoning (dataset)
GQA	Generalized Question Answering (dataset)
NLP	Natural Language Processing
TPU/GPU	Tensor/Graphics Processing Unit
CNN	Convolutional Neural Network

Nomenclature

Term	Description
Symbolic Reasoning	Logic-based reasoning using discrete, interpretable rules and knowledge structures
Sub-symbolic Reasoning	Pattern-based learning typically associated with neural networks
Hybrid Architecture	A system that integrates symbolic and sub-symbolic components for improved learning and reasoning
Representation Space	The structured format in which knowledge or data is encoded within a system
Knowledge Graph	A structured representation of knowledge using nodes and relations
Program Trace	A sequence of logic-based steps executed by a reasoning engine
Scene Graph	A structured graphical representation of objects and their relationships in an image
Grounding	Mapping symbolic representations to real-world data or perceptual inputs

CHAPTER 1
INTRODUCTION

1.1 OVERVIEW

Over the past few years, artificial intelligence (AI) has made major progress from rule-based symbolic systems to data-driven neural networks. In disciplines including natural language processing, computer vision, and robotics, this change has made amazing progress possible. Notwithstanding these achievements, present artificial intelligence systems still have major constraints, especially in their capacity to reason, grasp difficult situations, and base decisions on abstract ideas.

Dominating early AI research, symbolic artificial intelligence concentrated on clearly defined rules and logical structures to replicate human reasoning. These systems struggle with uncertainty and lack the capacity to learn from data; they shine at exact, deterministic decision-making. Conversely, inspired by the structure and purpose of the human brain, neural networks have shown quite great success in data-driven learning and pattern recognition. But they sometimes serve as "black boxes," lacking interpretability and transparency that would restrict their use in important sectors such healthcare and autonomous driving.

By combining the adaptive learning features of neural networks with the organised thinking of symbolic systems, neuro-symbolic artificial intelligence (NSAI) seeks to close this distance. Combining the best of both worlds, this hybrid approach aims to produce systems that can learn from challenging, unstructured data while reasoning precisely. NSAI presents the possibility for more strong, interpretable, and context-aware artificial intelligence systems able of human-like reasoning by merging symbolic logic with neural learning.

Among other important issues, NSAI systems seek to solve scalability, interpretability, and context awareness. These systems can accomplish challenging reasoning tasks, grasp cause-effect relationships, and more successfully adapt to new environments by combining explicit knowledge representation with data-driven learning than by only neural or symbolic systems alone.

This project seeks to present a thorough picture of NSAI's present situation together with its fundamental ideas, historical development, main architectures, useful applications, and continuous difficulties. The paper also looks at how standards and datasets help to assess NSAI systems, stressing the vital need of consistent assessment for developing the discipline. Emphasising the need of scalable architectures, consistent representations, and ethically good AI designs for reaching human-level intelligence, this work also points forth possible future directions for NSAI research.
the particular vulnerabilities of model generalization to minority classes.

1.2 OBJECTIVES

This research aims primarily to offer a thorough and critical study of the topic of neuro-symbolic artificial intelligence (NSAI). This study has as its primary objectives as follows:

a. Emphasising the integration of symbolic reasoning with neural learning, investigating the fundamental ideas and theoretical foundations of Neuro-Symbolic AI.

b. Following its origins from early symbolic systems to contemporary hybrid architectures, investigating the historical history and major benchmarks in the development of Neuro-Symbolic AI.

c. Examining the several architectural techniques used in NSAI—symbolic-neural integration, modular systems, and end-to–end differentiable architectures.

d. To show its practical influence by looking at NSAI’s useful applications in geoscience, robotics, healthcare, and autonomous systems, therefore proving its relevance in many spheres.

e. To provide possible remedies and pinpoint the difficulties and constraints NSAI faces—including scalability, interpretability, resilience, and knowledge integration—then

f. Emphasising the need of consistent assessment measures, one can evaluate the part of datasets and benchmarks in determining the performance of NSAI systems.

g. Emphasising unified representations, scalable learning methods, and morally good artificial intelligence designs will help one to offer ideas on the future directions of NSAI research.

h. By helping to clarify how NSAI can close the gap between perception and logic, hence furthering the creation of intelligent systems able of human-like thinking.

1.3 SCOPE

This work intends to systematically review the body of knowledge on Neuro-Symbolic Artificial Intelligence (NSAI), a fast developing field at the junction of symbolic reasoning and neural learning. With an eye towards assessing how hybrid artificial intelligence systems transcend the constraints of either purely symbolic or purely neural approaches, the project primarily aims to investigate the theoretical foundations, architectural developments, major applications, and evolving trends in NSAI.

Fundamental ideas including logic-based knowledge representation, neural encoding, differential reasoning, and hybrid learning systems are covered in the work It addresses significant architectures including Logic Tensor Networks, Neural-Symbolic VQA models, and graph-based reasoning systems as well as practical applications in fields including healthcare, geoscience, autonomous systems, and military artificial intelligence.

There is no experimental testing or application of any algorithms in this work. Rather, it methodically groups and synthesises ideas from 23 preprint and peer-reviewed research publications released between 2005 and 2025. The papers were chosen depending on their academic influence, applicability to NSAI, and portrayal of both classical and contemporary field developments including both modern and ancient technologies.

Along with a critical review of current issues including scalability, explainability, integration of heterogeneous knowledge, and computational overhead, the scope also points up interesting future directions including the creation of cognitive architectures and connection with generative artificial intelligence.

By means of this literature-based approach, the project intends to offer a consolidated knowledge base that can act as a reference for next academic research, system development, or multidisciplinary applications involving neuro-symbolic artificial intelligence.

CHAPTER 2
LITERATURE REVIEW

The foundation of this research project is the literature evaluation, which offers a thorough study of the body of current knowledge in the field of neuro-symbolic artificial intelligence (NSAI). It seeks to convey in this developing field of artificial intelligence a complete awareness of the fundamental ideas, historical evolution, and present tendencies. While investigating possible answers and future avenues for study, the paper also emphasises the important difficulties and constraints experienced by NSAI systems.

The literature review is split into several major sections, each with an emphasis on a particular facet of NSAI, therefore enabling a successful organisation of this study. This covers the historical history of symbolic and neural methods, the fundamental theoretical underpinnings of NSAI, the several architectures created to combine symbolic and neural reasoning, and the useful implementations of these systems in many spheres. Emphasising the need of standardised testing to guarantee the dependability and scalability of these technologies, the paper also explores the part of datasets and benchmarks in evaluating NSAI systems.

- **B. C. Colelough and W. Regli (2025) – Neuro-Symbolic AI in 2024: A Systematic Review**

Emphasising the evolution of Neuro-Symbolic AI (NSAI) from essentially symbolic systems to modern hybrid architectures including symbolic reasoning with deep learning, this work presents a comprehensive summary of the present situation of NSAI as of 2024. Although stressing the need of combining symbolic logic with data-driven learning for challenging decision-making, it also addresses the main challenges in NSAI including scalability, interpretability, and efficiency. The need of scalable architectures and consistent representation areas is underlined in order to close the distance between structured thinking and statistical learning. It also explores among other useful disciplines NSAI’s future possibilities in robotics, healthcare, and autonomous systems. This paper presented a basic perspective on the present trends and future possibilities of NSAI, so greatly augmenting the parts of this project on Historical Background, Approaches and Architectures, and Future Directions.

- **A. Sheth, K. Roy, and M. Gaur (2023) – Neurosymbolic AI – Why, What, and How**

This fundamental work addresses the advantages of hybrid architectures for interpretability, scalability, and transparency as well as the reasons for combining symbolic reasoning with neural learning. It provides a clear framework for understanding why reaching human-like reasoning and decision-making depends on NSAI. The authors underline the need of explainable artificial intelligence systems that can use both structured logic and data-driven learning, so providing a balanced approach of knowledge representation and decision-making. This work has been included in the Key Concepts and Foundations section of this project for its exhaustive study of the fundamental ideas of NSAI, including the trade-offs between interpretability and scalability and the need of including structured knowledge with statistical learning.

- **L. D. Raedt, S. Dumancic, R. Manhaeve, and G. Marra (2020) – From Statistical Relational to Neuro-Symbolic Artificial Intelligence**

Emphasising the need of relational thinking and structured knowledge in artificial intelligence, this work explores the change from just statistical techniques to hybrid NSAI systems. After considering the limits of simply statistical models, which sometimes suffer with interpretability and sophisticated reasoning, the authors propose hybrid approaches combining symbolic logic with probabilistic reasoning. Basic to modern NSAI designs, this work offers significant concepts including probabilistic logic programming and statistical relational learning. The part on Approaches and Architectures in this project emphasises the need of structured knowledge for challenging problem-solving and the need of hybrid approaches capable to balance statistical learning with logical reasoning.

- **A. d. Garcez and L. C. Lamb (2020) – Neurosymbolic AI: The 3rd Wave**

This work introduces NSAI as the third wave of artificial intelligence by combining symbolic logic with machine learning to generate more strong, interpretable systems.

Since they believe that only neural or symbolic approaches are insufficient to reach human-level reasoning and decision-making, the authors support a hybrid approach combining the benefits of both paradigms. This work addresses the limits of present artificial intelligence systems—including their lack of transparency and challenge in reasoning about complex, multi-step processes—by means of discussion. Since it provides a road map for building hybrid systems able of both statistical learning and logical reasoning, it is an essential reference for the sections of this project on the Historical Background and Approaches and Architectures.

- **M. K. Sarker, L. Zhou, A. Eberhart, and P. Hitzler (2021) – Neuro-Symbolic Artificial Intelligence: Current Trends**

Emphasising architecture, practical applications, and the challenges of merging symbolic thinking with neural learning, this work summarises NSAI's most recent advances. In disciplines including healthcare, robotics, and autonomous systems—where both interpretability and scalability are vital—the authors underline the growing relevance of hybrid models. Emphasising the need of efficient, scalable architectures capable to control real-world complexity, the paper also addresses the possible influence of NSAI on several sectors, including finance, manufacturing, and autonomous transportation. This work, which provides perceptive study of NSAI research's present situation and future prospects, appears in the Future Directions part of this project.

- **X. Zhang and V. S. Sheng (2024) – Bridging the Gap: Representation Spaces in Neuro-Symbolic AI**

This work addresses the crucial challenge of integrating symbolic and neural data by suggesting fresh representation spaces bridging the gap between structured logic and deep learning. The authors discuss the limits of current representation spaces—which sometimes struggle to capture both structured knowledge and statistical correlations—together with proposed hybrid techniques that can effectively combine these two kinds of data. This fundamental reference for the part on the Key Concepts and Foundations section of this project also underlines the need of creating homogeneous representation spaces for efficient learning and reasoning.

- **I. Hatzilygeroudis and J. Prentzas (2005) – Neuro-Symbolic Approaches for Knowledge Representation in Expert Systems**

Giving historical background for present NSAI systems, this early work underlines the need of combining symbolic and neural methods for knowledge representation in expert systems. Underlining the need of explainable artificial intelligence systems that can combine symbolic thinking with data-driven learning, the authors investigate the advantages of hybrid approaches in capturing both structured knowledge and statistical patterns. Now included in the Approaches and Architectures section of this project is this paper, which provides significant expert system analysis of NSAI's evolution and applications.

- **V. Belle (2024) – On the Relevance of Logic for AI, and the Promise of Neuro-Symbolic Learning**

Emphasising the need of symbolic thinking in generating interpretable, dependable artificial intelligence, this paper explores the philosophical and pragmatic effects of including logic into AI systems. While addressing the ethical concerns of NSAI including transparency, responsibility, and bias, the author advocates the need of combining symbolic thinking with statistical learning to generate more strong, explainable AI systems. Included in the section of this project on Challenges and Future Directions on Technical and Ethical Issues NSAI faces, this paper provides perceptive analysis of both.

- **L. Serafini and A. d. Garcez (2016) – Logic Tensor Networks: Deep Learning and Logical Reasoning from Data and Knowledge**

Logic Tensor Networks (LTNs) are presented in this basic work as a fundamental architecture for merging symbolic reasoning with neural learning. Combining the structured logic of first-order predicated calculus with the statistical learning capacity of deep neural networks, LTNs provide a single framework for thinking over both structured knowledge and unprocessed data. The authors present a formal approach for combining symbolic logic with machine learning such that artificial intelligence systems may control discrete, rule-based thinking and continuous, data-driven learning simultaneously. This approach is particularly useful for activities calling both exact logical reasoning and flexible, data-driven decision-making. This paper stresses the need of structured thinking in NSAI and its possibilities for generating interpretable, explainable artificial intelligence systems in the Approaches and Architectures and Knowledge Representation sections of your project .

- **J. Johnson, B. Hariharan, L. v. d. Maaten, L. Fei-Fei, C. L. Zitnick, and R. Girshick (2016) – CLEVR: A Diagnostic Dataset for Compositional Language and Elementary Visual Reasoning**

This work presents the CLEVR dataset as a required benchmark for evaluating NSAI systems' logical capability. Specifically designed to evaluate a model's ability for sophisticated, multi-step reasoning over structured visual environments, the CLEVR dataset provides an objective evaluation of a system's reasoning capacity. Since the authors provide a set of well-crafted visual questions needing models to combine spatial, relational, and logical reasoning, this is a helpful tool for assessing the interpretability and reasoning capacity of NSAI systems. Included in the section on Datasets and Benchmarks in this project, this paper emphasises the need of organised scene understanding for accurate reasoning in practical applications.

- **D. A. Hudson and C. D. Manning (2019) – GQA: A New Dataset for Real-World Visual Reasoning and Compositional Question Answering**

Emphasising intricate, compositional logic in natural settings, this work presents the GQA dataset—a real-world extension of the CLEVR dataset. Unlike CLEVR, which uses synthetic data, GQA is based on real-world images so providing NSAI systems a more realistic and demanding test. The authors underline the need of ordered scene representations and relational reasoning, thus this dataset is a fundamental tool for producing interpretable, real-world artificial intelligence systems. This project's section on Datasets and Benchmarks features it, stressing its applicability to practical NSAI applications and its contribution to visual reasoning's advancement of the field.

- **Z. Wan, C.-K. Liu, H. Yang, C. Li, H. You, Y. Fu, C. Wan, T. Krishna, Y. Lin, and A. Raychowdhury (2024) – Towards Cognitive AI Systems: a Survey and Prospective on Neuro-Symbolic AI**

This survey article addresses the possibilities for cognitive architectures in NSAI by means of symbolic reasoning combined with neural learning to increase context-awareness. Emphasising the challenges and opportunities in designing systems with human-like reasoning capacity, the authors provide a comprehensive overview of the present situation of cognitive artificial intelligence. Combining flexible, data-driven learning with structured, symbolic knowledge is shown to be relevant in order to generate artificial intelligence systems able of more human-like world understanding and reasoning. This road map for the future development of cognitive NSAI systems is provided by the sections of this project on Approaches and Architectures and Future Directions.

- **O. Bougzime, S. Jabbar, C. Cruz, and F. Demoly (2025) – Unlocking the Potential of Generative AI through Neuro-Symbolic Architectures: Benefits and Limitations**

The possibility of combining generative artificial intelligence with neuro-symbolic architectures to enhance both interpretability and scalability is discussed in this work. The authors underline the advantages of hybrid approaches for generating more robust, explainable AI systems that can produce complex outputs while preserving openness and control. This paper also addresses the limits of present generative artificial intelligence systems—including their lack of interpretability and difficulty in managing structured reasoning tasks—as well as their This work, which provides perceptive study of the opportunities for generative NSAI systems for pragmatic use, now appears in sections of this project on Future Directions and Applications.

- **D. H. Hagos and D. B. Rawat (2024) – Neuro-Symbolic AI for Military Applications**

This work integrates symbolic reasoning with real-time data processing for threat detection and autonomous system control, so improving situational awareness in military settings. The authors go over the difficulties in creating dependable, interpretable artificial intelligence systems for high-stakes military use, including the need of real-time decision-making, great dependability, and strong performance in dynamic, uncertain environments. This project's Applications section now features this work, proving NSAI's strategic value in defence technologies.

- **O. Fenske, S. Bader, and T. Kirste (2024) – Neuro-Symbolic Artificial Intelligence for Patient Monitoring**

Integrating sensor data with symbolic domain knowledge, this work addresses the application of NSAI in patient monitoring and human activity recognition, so enhancing real-time decision-making. To produce more accurate, interpretable systems for use in healthcare, the writers stress the need of combining symbolic thinking with statistical learning. Emphasising the vital part NSAI plays in enhancing patient care and healthcare decision-making, this paper has been included in the section on applications of this project.

- **W. Chen, X. Ma, Z. Wang, W. Li, C. Fan, J. Zhang, X. Que, and C. Li (2024) – Exploring Neuro-Symbolic AI Applications in Geoscience: Implications and Future Directions for Mineral Prediction**

Emphasising the interaction of symbolic geological rules with data-driven learning, this work explores the use of NSAI in geological modelling and mineral exploration. The authors discuss the challenges in building interpretable artificial intelligence systems for advanced geoscientific applications, including the need to control heterogeneous data and mix domain-specific knowledge with statistical models. Since the paper stresses NSAI's ability to improve the accuracy and dependability of geological forecasts, a good reference for the part of this project on applications is It presents a valuable case study of how hybrid artificial intelligence systems could be used for scientific discovery, so highlighting the practical impact of NSAI in earth sciences.

- **D. Hossain and J. Y. Chen (2025) – A Study on Neuro-Symbolic Artificial Intelligence: Healthcare Perspectives**

Especially in drug discovery, personalised medicine, and clinical decision support, this paper emphasises NSAI's promise in the healthcare sector. Emphasising the need of hybrid approaches that can combine structured medical knowledge with data-driven learning, the writers address the difficulties of creating interpretable, dependable AI systems for healthcare uses. A vital reference for the section of this project on Applications, where it is used to show the pragmatic advantages of NSAI in high-stakes, real-world applications, the paper also investigates the possible of NSAI for improving diagnostic accuracy and treatment efficiency.

- **Z. Wan, C.-K. Liu, H. Yang, R. Raj, C. Li, H. You, Y. Fu, C. Wan, S. Li, Y. Kim, A. Samajdar, Y. C. Lin, M. Ibrahim, J. M. Rabaey, T. Krishna, and A.**

Raychowdhury (2024) – Towards Efficient Neuro-Symbolic AI: From Workload Characterization to Hardware Architecture

The hardware-level optimisation of NSAI systems is examined in this work with an emphasis on effective architectures enhancing computational performance without sacrificing interpretability. The writers stress the need of creating specific hardware for NSAI systems, including hybrid processing architectures that can manage both symbolic reasoning and neural learning and neuromorphic chips and Emphasising the need of scalable, high-performance NSAI systems able to manage real-world complexity, this paper has been included in the sections of this project dedicated to Challenges and Future Directions.

- **K. Yi, J. Wu, C. Gan, A. Torralba, P. Kohli, and J. B. Tenenbaum (2019) – Neural-Symbolic VQA: Disentangling Reasoning from Vision and Language Understanding**

The NS-VQA framework is presented in this work as a more interpretable method to visual question answering since it divides visual perception from symbolic reasoning. The authors suggest a hybrid approach that can combine visual perception with structured reasoning after discussing the limits of simply neural approaches for visual reasoning, which frequently suffer with transparency and interpretability. This work has been included to the part on Datasets and Benchmarks in this project , where it emphasises the need of separating perception and reasoning for correct, interpretable artificial intelligence systems.

- **D. H. Hagos and D. B. Rawat (2024) – Neuro-Symbolic AI for Military Applications**

This work integrates symbolic reasoning with real-time data processing for threat detection and autonomous system control, so improving situational awareness in military settings. The authors go over the difficulties in creating dependable, interpretable artificial intelligence systems for high-stakes military use, including the need of real-time decision-making, great dependability, and strong performance in dynamic, uncertain environments. This project’s Applications section now features this work, which shows NSAI’s strategic significance in defence technologies.

- **J. Johnson, B. Hariharan, L. v. d. Maaten, L. Fei-Fei, C. L. Zitnick, and R. Girshick (2016) – CLEVR: A Diagnostic Dataset for Compositional Language and Elementary Visual Reasoning**

The CLEVR dataset is presented in this work as a necessary benchmark for assessing NSAI systems' reasoning capacity. Specifically meant to test a model's capacity for sophisticated, multi-step reasoning over structured visual environments, the CLEVR dataset offers a clear, objective assessment of a system's reasoning capacity. This is a useful tool for evaluating the interpretability and reasoning capability of NSAI systems since the writers present a set of well-crafted visual questions requiring models to combine spatial, relational, and logical reasoning. Emphasising the need of structured scene understanding for accurate reasoning in practical applications, this paper has been included in the part on Datasets and Benchmarks in this project.

2.1 HISTORICAL BACKGROUND

Combining the disciplined, rule-based logic of early symbolic systems with the adaptive, data-driven learning of modern neural networks, the history of Neuro-Symbolic AI begins with the fundamental notions of artificial intelligence itself. As the complexity of real-world situations became clear, this path mirrors the changing goals of artificial intelligence research, moving from simply logical approaches to more flexible, pattern-based techniques.

Early Symbolic Artificial Intelligence (1950s–1980s)

Often known as Good Old- Fashioned AI (GOFAI), symbolic artificial intelligence first surfaced in the 1950s and was distinguished by systems focused on explicit knowledge representation, formal logic, and rule-based reasoning. These early attempts were intrinsically interpretable since they sought to reproduce human thought using predetermined rules and ordered, human-readable symbols. Among the pioneering examples are DENDRAL (Lindsay et al., 1980), a rule-based expert system for chemical analysis; SHRDLU (Winograd, 1971), a system able of understanding and manipulating blocks through natural language; ELIZA (Weizenbaum, 1966), a program simulating psychotherapy conversations.

These systems battled some important issues, nevertheless, even with their remarkable early triumphs. They were brittle and difficult to scale since they needed thorough hand encoding of domain-specific rules. Moreover, the Frame Problem (McCarthy, 1969) – the difficulty of specifying all relevant knowledge needed to respond appropriately in dynamic environments – and the larger Common sense Knowledge Problem, which highlighted their incapacity to handle the vast, implicit background knowledge humans use effortlessly, limited symbolic systems [5], [12].

<u>Development of Sub-Symbolic AI (1980s – 2000s)</u>

By contrast, motivated by biological models of neuron processing, the sub-symbolic approach first surfaced in the 1980s. Driven by the comeback of artificial neural networks (ANNs), this wave stressed learning straight from data without any explicit symbolic representation. Foundational discoveries included the Perceptron (Rosenblatt, 1958), which showed that basic neuron-like structures could learn linearly separable patterns, the introduction of Backpropagation (Rumelhart et al., 1986), which enabled multi-layer networks to learn complex functions, and Hopfield Networks (Hopfield, 1982), which modelled associative memory.

These methods presented a fresh set of difficulties even if they excelled in statistical learning and pattern recognition. Among these was the Black Box Problem, which is the challenge in understanding the decision-making process among these networks. Unlike symbolic systems, which are naturally explainable, neural networks typically lack transparency, making it difficult to grasp their reasoning, a major constraint in sectors like healthcare and autonomous systems where responsibility is vital [6], [8].

<u>Early hybrid systems (1990s through 2010s)</u>

Early in the 1990s, academics started investigating hybrid systems after realizing the limits of only symbolic and essentially sub-symbolic methods. These attempts aimed to blend the adaptive learning powers of neural networks with the disciplined, rule-based thinking of symbolic artificial intelligence. Notable early work included hybrid logic networks and logic tensor networks (LTNs), which let symbolic logic be directly added into neural architectures to enable richer, more interpretable learning models.

Significant advancements in merging symbolic thinking with probabilistic models also occurred during this time, producing frameworks as Markov Logic Networks (MLNs) and Probabilistic Logic Networks. These systems provided a basis for contemporary neuro-symbolic systems since they bridged the gap between statistical thinking and organized logic [5], [6].

2010s – Present Modern Neuro-Symbolic AI

Driven by the need for artificial intelligence systems that can mix the flexibility of neural learning with the transparency and structure of symbolic reasoning, neuro-symbolic techniques have witnessed a rebirth of interest in the past ten years. Important developments include DeepProbLog (Manhaev et al., 2018), which combines probabilistic logic programming with deep learning, Neural Theorem Provers (NTPs) (Rocktäschel and Riedel, 2017), which enable neural networks to perform symbolic reasoning, and Neural Logic Machines (NLMs) (Dong et al., 2019), which extend these ideas to relational reasoning [6], [15], [18].

More recent developments have concentrated on building systems able to reason about intricate, unstructured data, hence bridging the gap between symbolic semantics and sub-symbolic learning. This covers methods include Graph Neural Networks (GNNs), which offer potent tools for relational reasoning, and Semantic Loss Networks, which utilize logic as a regularizing term to direct neural training. These systems advance the field towards generic, human-like intelligence, therefore reflecting the leading edge of neuro-symbolic artificial intelligence [2], [19].

2.2 KEY CONCEPTS AND FOUNDATIONS

Combining the disciplined, rule-based logic of symbolic systems with the adaptive, data-driven learning powers of neural networks, neuro-symbolic artificial intelligence (NSAI) reflects a forward-looking perspective. This mix seeks to close the distance between the strong pattern recognition capacity of contemporary artificial intelligence systems and human-like understanding. Appreciating NSAI's potential requires an awareness of its fundamental components: Representation Spaces, Knowledge Representation, Reasoning Mechanisms, the vital function of logic, and the special difficulties these systems encounter as they develop.

2.2.1 Representation Spaces

Representation spaces define how data is encoded, trans-formed, and handled inside an artificial intelligence system, therefore acting as the fundamental frameworks inside NSAI. These environments are important because they let the fluid, pattern-based learning of neural networks coexist with the disciplined logic of symbolic thinking. Based on their capacity to combine symbolic and neural data, Zhang and Sheng (2024) [6] propose a general classification for these representation spaces:

• Single-modal, non-heterogeneous: Designed to manage a particular form of data, such as text or images, single-modal, non-homogeneous solutions avoid integrating symbolic and neural aspects. These systems usually shine at specialized jobs when the data is homogeneous and well-defined.

• Multi-modal, non-homogeneous: Able to independently process several data kinds without actual integration between symbolic and neural components. Multimedia systems, where several data streams are handled independently, often make use of this method.

• Single-modal, heterogeneous: Focused on a single data type but blends symbolic and neural representations into a coherent framework, therefore producing a more comprehensive knowledge of the data.

• Multi-modal, heterogeneous: Processes varied data types while combining symbolic and neural representations, hence enabling deeper, context-aware data processing. These systems can manage difficult jobs where several data kinds need to be examined concurrently.

• Dynamic adaptive: Provides scalability and flexibility by changing its presenting techniques depending on the current task. In environmental conditions with fast changing data and complicated decision-making criteria, this method is especially helpful.

These categories show the increasing complexity of contemporary NSAI systems, which must strike strong performance by balancing interpretability, scalability, and task-specific adaptability [6].

	Single Modal Data	Multi-Modal Data	Neural Network OR Symbolic Logic Representation	Neural Network AND Symbolic Logic Representation
Single-modal and non-heterogeneous	✓		✓	
Multimodal and non-heterogeneous		✓	✓	
Single-modal and heterogeneous	✓			✓
Multimodal and heterogeneous		✓		✓
Dynamic adaptive	✓	✓	✓	✓

Fig 1: Neuro-Symbolic AI's classification by representation space (Zhang and Sheng, 2024)

2.2.2 Knowledge Representation

Fundamental to NSAI, knowledge representation (KR) offers the vital link between low-level brain activations and high-level symbolic thinking. It allows the integration of discrete, human-readable symbolic structures with continuous, data-driven neural representations, hence creating the backbone of intelligent systems able to both learn from data and reason logically.

Basic Structure and Challenges of Knowledge Representation:

Knowledge representation in NSAI functions as a link between the adaptive, flexible character of neural networks and the symbolic world of structured logic, therefore bridging their challenges. Combining the clarity and interpretability of symbolic structures with the data-driven learning of neural components makes sophisticated reasoning possible [7].

Two Primary Integration Approaches:

- Representational Integrations: These methods firmly combine symbolic logic with neural learning to produce unified knowledge bases using the strengths of both paradigms. By integrating the exact, interpretable reasoning of symbolic systems with the flexible, adaptive learning of neural networks, this kind of integration seeks to surpass the restrictions of simply connectionist approaches.

- Modular Integrations: By keeping a clear boundary between symbolic and neural components, modular integrations—which enable autonomous processing and well-defined interfaces. This approach is perfect for complicated systems where several components must cooperate without close coupling since it supports transparency, scalability, and adaptability [7].

Functional Approaches within Modular Systems

Modular integrations can be further categorized based on the degree of interconnection and the flow of information:

- Passively Coupled: Systems with loose connections—usually communicating through shared files or external data transfers—allow for independent operation by means of passively coupling.
- Actively Coupled: Tighter integration with shared memory and synchronized processing from actively coupled systems helps to provide more direct and responsive interactions.
- Interleaved: High-level interactions called interleaved between direct function calls and sophisticated communication protocols allow real-time information flow [7].

Subcategories of Representational Integrations

Some systems focus more on the symbolic component within representational integrations, applying neural methods to improve tasks, while others give the neural component top priority and include symbolic rules as supporting structures within essentially neural frameworks [6].

Advantages of Knowledge Representation in NSAI

Particularly suited for uses requiring thorough explanations and systematic thinking, symbolic knowledge representation offers clarity, modularity, and transparency. Conversely, neural components complement the disciplined thinking of symbolic systems to produce more strong, intelligent models by providing flexibility, efficiency, and the capacity to learn directly from data [7].

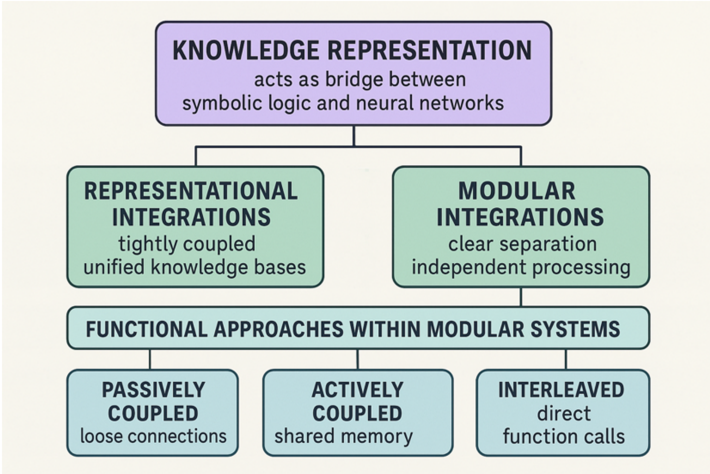

Fig 2: Knowledge Representation in Neuro-Symbolic AI: Integration of symbolic logic and neural networks through representational and modular approaches.

2.2.3 The Role of Logic in Neuro-Symbolic Systems

NSAI is fundamentally based on logic, which also provides the framework required for sophisticated thinking and decision-making. Belle (2024) contends that although symbolic logic is old, it is still very important for developing strong artificial intelligence systems. He underlines that a crucial capacity for artificial intelligence systems functioning in real-world situations full of uncertainty and incomplete knowledge is symbolic logic's ability to encapsulate uncertain and probabilistic relationships.

Key requirement in high-stakes applications including healthcare, banking, and autonomous systems, explainability is also supported by logical frameworks. Logic-based systems provide unambiguous, human-readable decision routes unlike simply neural models, which may serve as "black boxes," hence they are indispensable for applications where responsibility is paramount [8].

2.3 APPROACHES AND ARCHITECTURES

Seeking to close the gap between the flexible, data-driven learning capacity of neural networks and symbolic reasoning, which is noted for its clarity and correctness, neuro-symbolic artificial intelligence (NSAI) Combining the greatest aspects of both paradigms, this hybrid approach seeks to produce artificial intelligence systems able to reason about the world with the accuracy of logic and adapt to new input, including neural models. This part explores several NSAI structures and techniques, each suitable for some problems in knowledge representation, learning, and reasoning.

2.3.1 Symbolic-Neural Integration

Designed on symbolic-neural integration, several NSAI systems tightly combine logical reasoning and neural learning to produce coherent models. One well-known example is the 2016 Serafini and Garcez showed **Logic Tensor Network (LTN)** framework. Directly including first-order logic into neural topologies, LTNs handle continuous inputs as well as structured, symbolic data. This mix serves applications including autonomous robots, scientific data processing, and natural language understanding where correct reasoning and flexible learning are critical [9].

The **Neuro-Symbolic Concept Learners (NSCL)**, another well-known method, combine explicit symbolic reasoning with brain sensing. These models shine on challenging tasks like visual question answering (VQA), in which case inferring relationships between objects in a scene is quite important. For structured thinking, for example, NSCLs beat solely neural models depending on datasets such **CLEVR** and **GQA**.

Recent developments in this field also involve probabilistic models as **DeepProbLog**, which extends symbolic logic to control uncertainty. Among other practical ones, these models fit applications including robotics, medical diagnostics, and financial predictions. These models assist systems to properly manage noisy or ambiguous inputs by integrating deep learning with probabilistic thinking [6], [15].

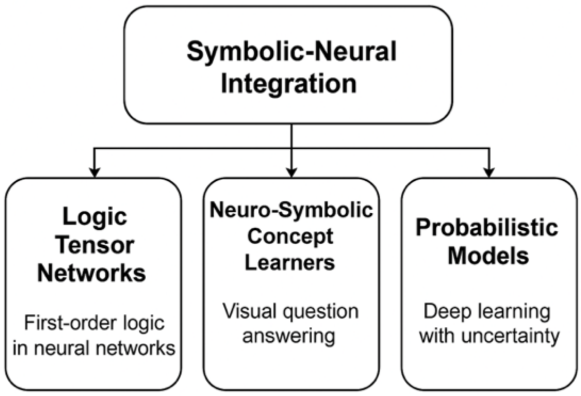

Fig 3 : Neuro Symbolic Integration Architecture

2.3.2. Modular and Distributed Architectures

Clear distinction between neural and symbolic elements preserved by modular architectures increases scalability and transparency. Within these systems, independent, the neural sensory modules and symbolic thinking engine function interact via transparent interfaces. Systems needing exceptional interpretability and simple explanations mostly rely on this architecture. Paul et al. (2024) for instance created a modular design separating symbolic reasoning from perceptual data processing so improving transparency and adaptability [14].

Distributed designs enable neural and symbolic components to run over several computational nodes, hence advancing this idea. This method is perfect for applications such autonomous driving, smart city management, and main financial systems since it supports large-scale, real-time processing. These ideas have produced adoption of foundation models including GPT-4, which include pre-trained knowledge bases for quick, context-aware reasoning [15].

Furthermore greatly increasing the efficiency of these systems is the development of neurosymbolic processors and specialized artificial intelligence chips allowing rapid, large-scale reasoning across distant networks. In important areas including industrial automation and defense systems, these developments allow real-time decision making [15].

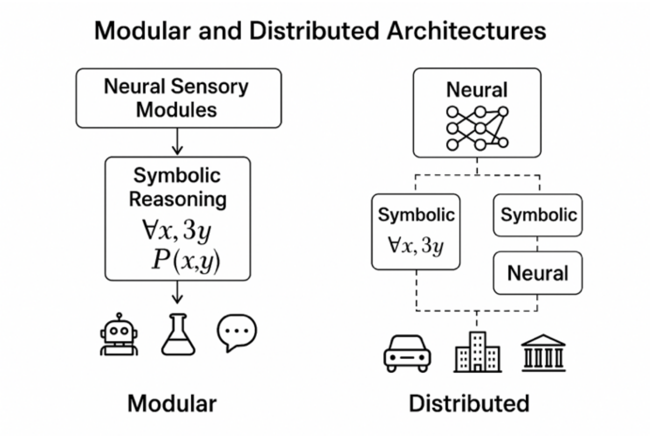

Fig 4: Modular and Distributed Architecture

2.3.3. End-to-End Differentiable Architectures

End-to- end designs directly include symbolic reasoning components into neural networks, therefore optimizing gradient descent of the entire system. Two such systems are **neuro-symbolic concept learners (NSCLs)** and **logic tensor networks (LTNs**). Together, they optimize neural and symbolic traits so allowing exact, context-aware reasoning [9].

These designs well match robotics and autonomous systems since environmental adaptation depends on constant learning. This method works well for autonomous drones and robotic surgery systems, for example, which must make decisions in real time depending on both specified guidelines and learnt experiences [6].

2.3.4. Systems of Neural-Symbolic Memory

Using neural networks' generalization capacity, neural-symbolic memory systems store and access organized symbolic data. The incorporation of memory modules directly reflecting symbolic information by these systems makes long-term planning and sophisticated multi-step decision-making feasible. Usually, benchmarks like **CLEVR** and **GQA** are used to assess these systems since they require both visual sense and organized thought [10], [11].

Recent advances like episodic memory systems, which let more complex decisions be made in dynamic environments, help artificial intelligence to remember and recall past events for long stretches of time. Dependencies on this capacity span military strategic planning, disaster assistance, and smart traffic management [15].

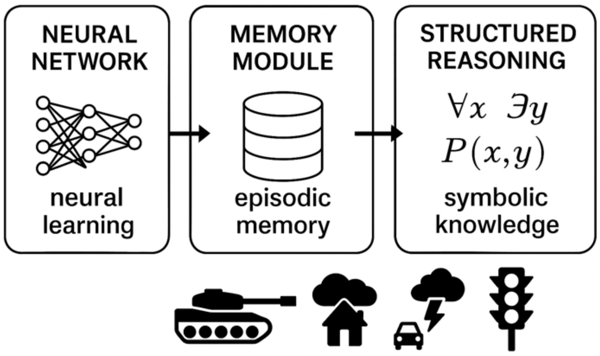

Fig 5: Systems of Neuro Symbolic Memory

2.3.5. Cognitive Architectures for Neuro-Symbolic AI

Cognitive architectures meant to replicate human-like thinking mix symbolic logic with neural learning in a physiologically reasonable manner. Many times, these systems imitate difficult cognitive tasks including working memory, episodic memory, and attention strategies. To provide a more all-encompassing approach of artificial intelligence, Wan et al. (2024) propose a cognitive architecture combining symbolic reasoning with neural pattern recognition) [12].

Foundation models are becoming more and more crucial in cognitive architectures since they may integrate deep learning and vast amounts of symbolic knowledge to raise context awareness and long-term thinking, claims Cunnington et al. (2024). Very intelligent systems capable of comprehending and reacting to challenging, real-world events require this integration [13].

Despite significant progress, several challenges remain in designing effective neuro-symbolic architectures:

- Scalability: As the complexity of symbolic reasoning increases, maintaining efficiency becomes challenging.
- Interoperability: Ensuring smooth communication be- tween symbolic and neural components remains a critical hurdle.

- Explainability vs. Flexibility: Balancing interpretability with the flexibility of neural networks is a persistent issue.
- Knowledge Acquisition Bottlenecks: Encoding human knowledge into symbolic form is labour-intensive and error-prone [14], [15].

2.4 CHALLENGES IN NEURO-SYMBOLIC AI

Despite the major developments in Neuro-Symbolic AI (NSAI), many basic issues remain affect its scalability, interpretability, robustness, and practical relevance. By means of overcoming these challenges, NSAI systems will be able to reach their full potential and develop human-like reasoning capability. Generally speaking, the main difficulties can be classified in relation to scalability and efficiency, explainability and interpretability, robustness and generalisation, knowledge acquisition and representation, ethical and strategic issues.

2.4.1 Scalability and Efficiency

Scalability presents one of NSAI's primary challenges. Keeping computational efficiency becomes somewhat challenging as symbolic thinking gets more complicated. Usually consuming significant computational resources, symbolic systems depend on examination of many logical rules and limits. Integration of high-dimensional continuous neural network input aggravates this complexity even more. Effective scaling these systems to handle practical issues is still a major challenge since even small changes in problem complexity could cause exponential increase in computational need [15].

Recent attempts on this problem have concentrated on optimising hybrid structures to lower their processing overhead and creating more effective symbolic reasoning systems. For instance, developments in **Graph Neural Networks (GNNs)** and **Differentiable Logic Systems** have showed promise in lowering the processing cost of symbolic reasoning while preserving outstanding degrees of accuracy and interpretability [6], [15].

2.4.2 Explainability and Interpretability

In important uses such autonomous systems, banking, and healthcare, artificial intelligence systems must be understandable. Unlike essentially neural models, which could operate as "black boxes," NSAI systems are supposed to offer explicit, human-readable justifications for their choices. While achieving this degree of openness is difficult, occasionally the orderly, traceable patterns observed in merely symbolic systems are absent when combining symbolic thinking with neural learning as the constant quality of brain representations is lacking [14].

Efforts to increase the interpretability of NSAI systems have produced **Logic Tensor Networks (LTNs)** and **Neural Theorem Provers (NTPs)** which combine logical reasoning with gradient-based optimisation to generate more interpretable outputs. Researchers have also investigated hybrid approaches that precisely separate the symbolic from the neurological elements, therefore facilitating more exact explanations and simpler, straight forward decision-making [14].

2.4.3 Robustness and Generalization

Robustness and generalisation remain significant challenges for NSAI systems especially in dynamic, real-world environments where data can be noisy, absent, or rather unpredictable. Unlike basically neural systems, which can generalise effectively from large volumes of training data, NSAI systems can find it difficult to adapt to new, unforeseen conditions without major re-engineering. The basic trade-off in hybrid artificial intelligence systems, that between accurate, rule-based thinking and flexible, data-driven learning, adds to aggravation of this problem [6], [14].

To manage this, researchers are developing more robust designs that can change with the environment while maintaining their interpretability and logical coherence. This addresses how **Meta-Learning, Transfer Learning, and Reinforcement Learning** might be applied to increase NSAI system versatility over many tasks and domains [13], [19].

2.4.4 Knowledge Acquisition and Representation

Encoding human knowledge in symbolic representation is a major obstacle for NSAI systems many times labour-intensive and error-prone. Unlike neural networks, which can learn straight from data, symbolic systems depend on well selected knowledge bases that exactly show the relationships and constraints inside a given topic. Time-consuming and resource-intensive, this process reduces the scalability of symbolic approaches in pragmatic applications [5], [19].

Recent advances in **Automated Knowledge Extraction** and **Differentiable Knowledge Bases** strive to address this challenge by automating the process of translating unstructured data into structured, symbolic representations. These methods use machine learning and natural language processing (NLP) methods to extract relevant knowledge from unstructured data, therefore lowering the requirement for hand rule construction [6].

2.4.5 Ethical and Strategic Considerations

For NSAI, ethical concerns provide a significant challenge particularly in areas of privacy, responsibility, and bias. As these systems find increasing general use in important applications, transparency, fair, and morally good artificial intelligence becomes more essential. This includes issues including algorithmic bias, data privacy, and possible use in industries including military applications and spying [10], [17].

These problems are being addressed by researchers looking at frameworks for Explainable AI (XAI) and Ethical AI Design—which aim to deliver technically sound systems with social conscience—hereby. This means embedding ethical problems into NSAI system architecture and execution so that they complement more broad society values and practices [20], [8].

2.5 APPLICATIONS OF NEURO-SYMBOLIC AI

Great possibilities for neuro-symbolic artificial intelligence (NSAI) in transforming a great spectrum of real-world applications have shown by combining the disciplined reasoning of symbolic systems with the fluid learning of neural networks. This hybrid approach has particularly been helpful in fields where both interpretability and data-driven learning are rather important. **Military systems, healthcare, geoscience and mineral prediction, patient monitoring and human activity recognition** constitute main areas of application.

Healthcare Applications

NSAI is becoming ever more important in the healthcare industry, where fast, accurate, clear decision-making is absolutely needed. These devices allow doctors more overall awareness for diagnosis and treatment planning by combining real-time patient data with clinical experience. For instance, Hossain and Chen (2025) underline the part NSAI plays in the **evolution of drugs** since integrating symbolic thinking with machine learning can more precisely find possible therapeutic options than more traditional approaches. High-throughput experimental data combined with biological knowledge lets these systems accelerate the creation of new medical treatments and raise the efficacy of clinical trials [20].

Also successes for NSAI have been early disease diagnosis and patient monitoring automation. Using **Logic Tensor Networks (LTNs)**, early warning signals discovered; expected disease progression identified; patient data anomalies discovered. Combining the precision of symbolic thinking with the adaptability of neural learning helps healthcare systems to keep interpretability and help in understanding of noisy, complex data. This ability is rather critical in clinical decision support systems, where accuracy and openness are highly valued [20].

Geoscience and Mineral Prediction

NSAI is addressing among difficult geoscience problems mineral exploration and resource management. Chen et al. (2024) investigate how data-driven learning combined with geological domain knowledge might improve mineral prediction accuracy by NSAI systems. To find possible mineral-rich zones, these systems search vast, heterogeneous databases including geochemical analyses, remote sensing images, geological maps, and geochemistry. Unlike some conventional machine learning models which sometimes suffer with sparse and noisy data, NSAI can include expert knowledge by symbolic representations, so improving both model interpretability and robustness [2].

Combining physical rules with data-driven insights enables NSAI systems to replicate intricate geological events including the development of mineral deposits. This method not only raises prediction accuracy but also gives geologists better understanding of the fundamental causes of mineralisation, which is required for directing appropriate exploration activities [2].

Military Applications

In military operations when real-time decision-making, threat detection, and autonomous system control are absolutely vital, NSAI shows great promise. Underlining the use of NSAI for raising situational awareness where these systems can mix many data sources—such as sensor inputs, satellite imagery, and battlefield reports—into a coherent operational picture are Hagos and Rawat (2024). By means of this integration, military leaders can spot possible hazards, automatically process satellite images for enemy movement detection, and offer real-time recommendations for best action. These systems' symbolic component ensures that decisions are reasonable and auditable, so lowering the likelihood of unanticipated effects in high-stakes settings [17].

NSAI finds application for fields including autonomous weapon systems, cybersecurity, and military logistics as well as for disciplines including Combining symbolic thinking with neural networks, for example, can produce strong cybersecurity systems able of fast spotting and neutralising cyberattacks. This hybrid approach not only promotes the development of intelligent training systems but also helps to replicate demanding combat scenarios, so enhancing military operational effectiveness and readiness [17].

Patient Monitoring and Human Activity Recognition

Another absolutely vital discipline where NSAI has shown great success is patient monitoring. Analysis of real-time data guarantees patient safety and high standard of treatment. With a system combining symbolic domain knowledge with sensor data, Fenske et al. (2024) track hospital patient activity. This method gives fall detection, real-time vital sign monitoring, and major medical event identification—so arming the medical staff with practical knowledge to enhance patient outcomes [18].

Important problems in patient monitoring including data heterogeneity and low-latency processing needs also are addressed by these systems. By combining neural networks for perception with symbolic reasoning for high-level understanding, NSAI provides a more whole and logical solution for patient care that lowers risk of false alarms and enhances clinical decision-making [18].

Future Directions and Emerging Applications

Among other important fields, NSAI is under development and finding use in **robotics, natural language processing, finance, and autonomous driving**. Constant research seeks to enhance these systems to increase scalability, interpretability, and efficiency so they might meet the needs of ever more demanding real-world projects. This addresses the evolution of more robust learning algorithms, improved reasoning capacity, and better integration of symbolic and neural components for really intelligent systems [22].

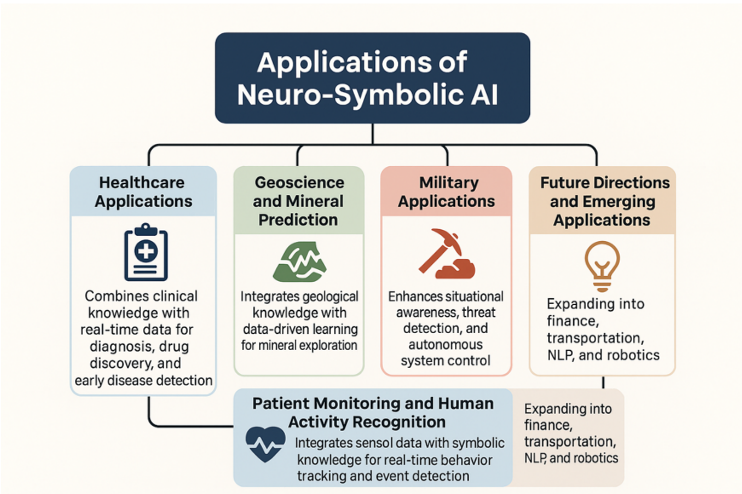

Fig 6: Applications of Neuro-Symbolic AI

2.6 DATASETS AND BENCHMARKS FOR NEURO-SYMBOLIC AI

To assess their reasoning, perception, and language understanding capability, neuro-symbolic artificial intelligence (NSAI) systems depend on particular datasets and benchmarks. Unlike conventional machine learning datasets, these benchmarks are intended to test both symbolic reasoning and neural perception, so enabling models to efficiently mix data-driven learning with structured logic. Three main datasets—CLEVR, GQA, and NS-VQA—each with unique challenges and insights on NSAI system performance—have grown to be indispensable benchmarks in this field.

CLEVR Dataset

Synthetic benchmark meant to evaluate visual reasoning capacity of artificial intelligence models is the **CLEVR (Compositional Language and Elementary Visual Reasoning)** dataset. Covering a broad spectrum of reasoning challenges including attribute recognition, spatial correlations, counting, logical comparisons, and multi-step reasoning, it has 100,000 images and over a million computer-generated questions [10].

Important elements of the CLEVR archive consist in:

Synthetic Scenes: Simple 3D-generated objects with well-defined properties including colour, shape, size, and material in synthetic environments make up the dataset. This controlled environment helps to eliminate the uncertainty sometimes present in natural images, so enabling exact evaluation of logical capacity.

Functional Programs: Every CLEVR question is answered as a functional program outlining the rational paths needed to get to the right response. This framework gives a clear evaluation system and enables models to follow demanding logical sequences.
Bias Reduction: By means of rejection sampling and structured data generation, CLEVR reduces question-conditional biases so guaranteeing that models cannot rely on statistical shortcuts to solve problems without real thought.

Hierarchical Reasoning: The dataset is particularly designed to test hierarchical thinking, thus models have to grasp advanced relational logic and multi-step dependencies.

Among CLEVR assignments are more complex compositional searches (e.g., “Are there more red cubes than blue spheres?”) and basic attribute identification (e.g., “What colour is the cylinder?”). These several kinds of tasks make CLEVR a necessary benchmark for assessing the reasonability of NSAI systems [10].

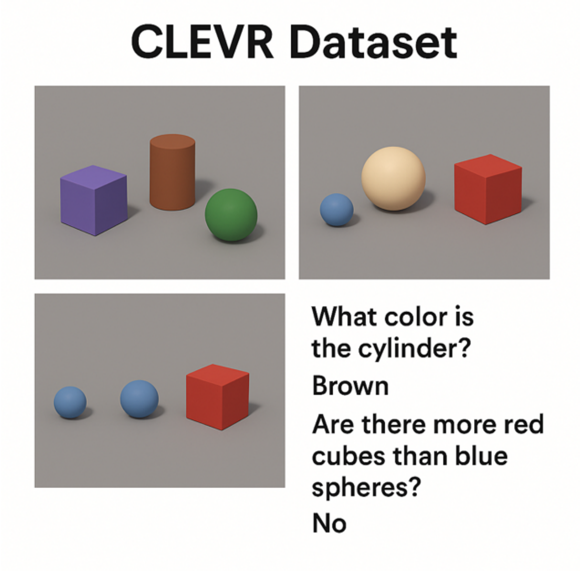

Fig 7: CLEVR Dataset

<u>GQA Dataset</u>

Designed by Hudson and Manning (2019), the GQA (Generalised Question Answering) dataset introduces more varied and challenging reasoning challenges while extending the ideas of CLEVR to real-world scenarios. Including more than 22 million questions depending on natural images seriously complicates visual understanding tasks [11].

Important elements of the GQA collection consist in:

Real-World Images: Developed on actual images from the Visual Genome collection, GQA offers a more realistic, richer testing environment than CLEVR, which makes use of synthetic data.

Scene Graph Annotations: Every image is shown as a structured scene graph recording objects, properties, and connections, so enabling more exact control over the logical structure and semantics of the searches.

Compositional Reasoning: Structured templates that inspire compositional thinking by means of which models must interpret demanding spatial and semantic connections help to develop GQA questions.

Bias Mitigation: Modern methods are used in the dataset to minimise statistical biases by means of tuned smoothing methods balancing answer distributions and so minimising overfitting to common patterns.

Extensive Evaluation Metrics: By including fresh performance criteria including consistency, grounding, and plausible behaviour, GQA presents a more sophisticated picture of model capacity than only basic accuracy [11].

The GQA dataset drives models to combine scene context, object relationships, and linguistic patterns into a coherent framework going beyond basic object recognition.

NS-VQA Dataset

Presented by Yi et al. (2019), the **NS-VQA (Neural-Symbolic Visual Question Answering)** dataset develops on the CLEVR framework but brings a more explicitly structured approach of reasoning. It provides unambiguous semantic representations that separate experience from reason, so enabling to untangle vision and cognition [21].

Key elements of the NS-VQA dataset consist in:

Structured Scene Representations: The highly detailed structural drawings of the images split scene context, object properties, and spatial relationships. This method guarantees quite reasonable cognitive processes and helps to lower uncertainty.

Program Execution for Reasoning: Every question corresponds to a deterministic program trace, hence allowing exact study of model reasoning mechanisms and unambiguous decision-making.

Efficient Learning: Symbolic methods are shown to be effective since NS-VQA systems almost perfect reasoning accuracy with much smaller training sets than conventional end-to-----end neural models.

Interpretability and Robustness: The emphasis on symbolic thinking in the dataset helps models to be strongly interpretable, which helps them to precisely, step-by-step explain their outputs—essential for high-stakes applications including healthcare and autonomous systems [21].

The NS-VQA dataset emphasises the benefits of ordered, symbolic thinking over only neural approaches, so underlining the need of hybrid architectures in obtaining human-like understanding.

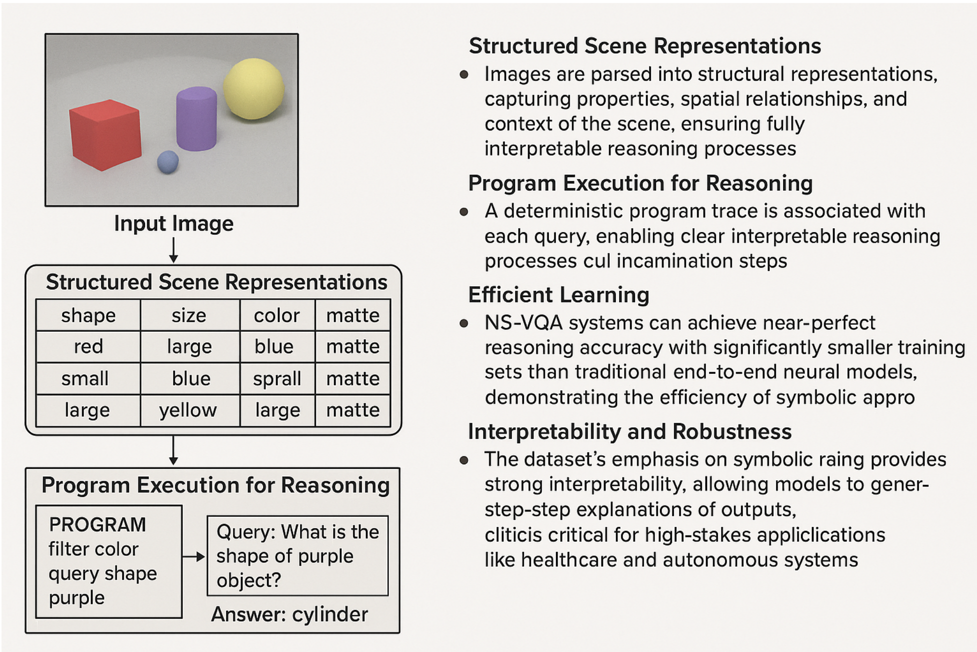

Fig 8: NS-VQA Dataset

<u>Comparison and Emerging Trends</u>

Covering many facets of the reasoning spectrum, these databases taken together offer a complete basis for assessing NSAI systems. GQA spans this approach to real-world scenarios and NS-VQA stresses transparent, program-based thinking; CLEVR focusses on controlled, synthetic thinking. Continuous research aiming at further integration of these strengths searches for benchmarks balancing interpretability, scalability, and practical relevance.

2.7 FUTURE DIRECTIONS FOR NEURO-SYMBOLIC AI

As the field of Neuro-Symbolic AI (NSAI) grows, many significant areas of research are opening doors meant to overcome the present limitations of this hybrid approach and forward the evolution of more capable, interpretable, and scalable AI systems. **Unified Representations and Symbol Grounding, Scalable Learning and Efficient Architectures, Enhanced Explainability and Interpretability, Ethical and Societal Considerations, and Real-World Applications and Domain-Specific Advances** should all take front stage in next work.

Unified Representations and Symbol Grounding

One of NSAI's main goals going forward is the development of unified representation spaces that can easily mix symbolic and neural elements. Many times depending on different, loosely coupled representations, current systems restrict their capacity to reason about complex, multi-modal data. Development of integrated frameworks capable of concurrently processing unstructured neural embeddings and structured symbolic knowledge should be the focus of future research. This will call for advances in computational architecture and representational theory to ensure that systems may grasp and control abstract ideas in a human-like manner [6], [19].

Another great challenge still is symbol grounding. If NSAI systems are to approach human-level knowledge, they must be able to link abstract symbols with actual sensory data. This requires the development of models able to dynamically link symbolic representations to actual, perceptual experiences, so bridging the gap between high-level thinking and low-level perception [6].

Scalable Learning and Efficient Architectures

Scalability remains one main obstacle to NSAI's general acceptance. The high-dimensional data processing capability of neural networks and the combinatorial complexity of symbolic reasoning provide main challenges for present designs. To aid with this, researchers are looking at more scalable, efficient designs that can manage huge, heterogeneous datasets while maintaining interpretability and robustness. This covers hardware accelerators, best neural-symbolic pipelines, and energy-efficient learning algorithms [15].

Emerging technologies including quantum neural-symbolic systems and neuromorphic computing especially excite greatly accelerating NSAI system speed and efficiency. These techniques allow real-time reasoning in dynamic, complex environments by seeking to replicate the parallel processing capacity of the human brain, so reducing the computational overhead connected with conventional neural-symbolic designs [22]..

Enhanced Explainability and Interpretability

Explainability still forms the pillar of NSAI, fundamental for building confidence in AI systems applied in high-stakes sectors including healthcare, finance, and autonomous systems. Future research should focus on transparent intermediate representations so that human users and downstream AI components may understand and validate decision-making. This covers developing human-readable explanations from novel approaches for following decision paths and challenging neural-symbolic interactions [8], [14].

Moreover, a hopeful path towards more interpretable NSAI systems is shown by combining symbolic thinking with foundation models. By means of pre-trained knowledge, these models can generate more ordered, significant outputs, so improving transparency and dependability. Furthermore, present research in neuro-symbolic causal reasoning shows promise in producing models that simplify cause-and- effect interactions inside complex systems, so enhancing interpretability and performance [13], [22].

Ethical and Societal Considerations

As NSAI systems get more capable, their ethical ramifications must be carefully considered. This covers addressing potential prejudices, guaranteeing data privacy, and setting fail-safe mechanisms to prevent unexpected outcomes. Researchers are looking at under the concept of “explainable responsibility,” whereby NSAI systems have to offer comprehensive, auditable documentation of their decision-making practices to ensure adherence to ethical standards [17], [20].

Moreover needed are standardised benchmarks and assessment tools to assess the ethical impact of NSAI technologies, so ensuring their fair and safe operation in useful settings. This approach aims to generate AI systems that are not only interpretable but also accountable for their actions, so reducing the possibility of abuse and unintended results [20].

Real-World Applications and Domain-Specific Advances

At last, significant advancements in actual applications will be necessary for the practical implementation of NSAI systems. The main priorities of next research should be customising NSAI systems to fit the particular needs of different sectors and applying domain-specific knowledge to increase performance and dependability. This covers cognitive computing, human-AI interaction, and collaborative robotics where NSAI systems have to fit exactly in demanding real-world environments [12].

As NSAI develops, research has to concentrate on solving these issues and creating dependable, scalable, ethically sound systems able of reasoning and comprehension at the level of people. This will demand a multimodal approach blending concepts from symbolic logic, machine learning, cognitive science, and neuroscience [13], [22].

CHAPTER 3
METHODOLOGY

This section describes the entire approach we used to do the literature review for our Neuro-Symbolic AI (NSAI) project. Our method was designed to guarantee complete coverage of historical background, fundamental ideas, key architectures, real-world applications, critical challenges, datasets, and future directions considering the varied and fast changing character of the field. The process consisted in several phases including literature collecting, paper selection, thematic categorisation, content extraction, and structured synthesis in order to guarantee a thorough and in-depth knowledge of the field.

3.1 Literature Collection

Our first task was compiling relevant NSAI research papers. We merged academic databases including IEEE Xplore, arXiv, SpringerLink, and Google Scholar to find high-quality, peer-reviewed papers. The search included both basic ideas and current developments covering the years 2005 through 2025. Among the key search terms were "Neuro-Symbolic AI," "Logic Tensor Networks," "Symbolic AI," "Deep Learning," "Knowledge Representation," "visual question answering," "cognitive AI," "hybrid AI architectures."

Emphasising a wide range of topics from early symbolic reasoning systems (Hatzilygeroudis and Prentzas, 2005) to contemporary hybrid architectures like Logic Tensor Networks (Serafini and Garcez, 2016) and NS-VQA (Yi et al., 2019), we first compiled over 50 papers. Crucially important datasets including GQA (Hudson and Manning, 2019) and CLEVR (Johnson et al., 2016) which evaluate NSAI systems' reasoning capacity were also part of this collection. Using Zotero for reference management helped us to properly organise and monitor the acquired papers, so ensuring accurate citation and seamless integration into our final project report.

3.2 Paper Selection and Screening

After collecting the initial set of papers, we conducted a rigorous screening process to identify the most relevant and impactful studies. This involved evaluating each paper based on its contribution to the core themes of the project, including foundational concepts, architectural innovations, real-world applications, and emerging trends. We prioritized papers that introduced innovative theoretical frameworks, such as 'Logic Tensor Networks' (Serafini and Garcez, 2016) and 'Neurosymbolic AI: The 3rd Wave' (Garcez and Lamb, 2020), as well as those that presented critical datasets like CLEVR (Johnson et al., 2016) and GQA (Hudson and Manning, 2019). Papers that addressed real-world applications, like 'Neuro-Symbolic AI for Military Applications' (Hagos and Rawat, 2024) and 'Neuro-Symbolic AI in Healthcare' (Hossain and Chen, 2025), were also prioritized for their practical relevance.

We categorized the selected papers into the following thematic groups:

- **Foundational Papers** – Early works that established the basic principles of NSAI, including symbolic logic, knowledge representation, and early hybrid systems. Examples include 'Neuro-Symbolic Approaches for Knowledge Representation in Expert Systems' (Hatzilygeroudis and Prentzas, 2005) and 'From Statistical Relational to Neuro-Symbolic AI' (Raedt et al., 2020).

- **Architectural Innovations** – Papers introducing novel architectures for integrating symbolic reasoning with neural learning, such as 'Logic Tensor Networks' (Serafini and Garcez, 2016) and 'Neurosymbolic AI: The 3rd Wave' (Garcez and Lamb, 2020).

- **Application-Focused Papers** – Studies demonstrating the real-world impact of NSAI in fields like healthcare (Hossain and Chen, 2025), military systems (Hagos and Rawat, 2024), and geoscience (Chen et al., 2024).

- **Challenge-Oriented Papers** – Research addressing the technical and ethical challenges of NSAI, including scalability, interpretability, and bias, such as 'On the Relevance of Logic for AI' (Belle, 2024) and 'Towards Efficient Neuro-Symbolic AI' (Wan et al., 2024).

- **Future Directions** – Papers discussing emerging trends and the potential for future breakthroughs, including ‘Unlocking the Potential of Generative AI through Neuro-Symbolic Architectures’ (Bougzime et al., 2025) and ‘Towards Cognitive AI Systems’ (Wan et al., 2024).

3.3 Literature Analysis and Categorization

Following the first screening, we categorised the selected papers according to themes to provide a clear structure for the literary review. Important trends, repeating motifs, and research gaps needed this classification. For example, whereas more recent studies like those by Hossain and Chen (2025) were placed in the Applications section for their real-world impact, foundational papers like those by Garcez and Lamb (2020) and Serafini and Garcez (2016) were grouped under Foundational Concepts. This thematic structure helped us to link creative ideas with early theoretical work so building a cogent narrative for the literature review.

3.4 Content Extraction and Synthesis

Then one could gather thorough understanding, ideas, and findings from every paper. This addressed significant contributions, creative ideas, useful applications, and difficult technical issues. We carefully review every paper to understand its primary contributions and observe how different approaches addressed specific NSAI concerns. Works including “GQA: A New Dataset for Real-World Visual Reasoning” (Hudson and Manning, 2019) were included for their contributions to dataset design and benchmark evaluation; papers including “Logic Tensor Networks” (Serafini and Garcez, 2016) were highlighted for their creative approach to combining symbolic reasoning with deep learning.

3.5 Writing and Structuring the Literature Review

Once the material was acquired, we set it in order to ensure a logical flow from basic ideas to practical applications and future directions. Every component was painstakingly crafted to complement the one before it presents a complete view of the field. We included careful studies of significant architectures, critical datasets, and useful applications to ensure that all major topics were covered without repeated coverage.

3.6 Reference Management and Citation

Zotero helped us to correctly arrange our sources, generate accurate citations, and maintain consistent formatting all through the effort, so benefiting our reference management. We set papers by theme using Zotero's collection tool to ensure appropriate citation of every reference in the final project report. Along with checking citation accuracy, looking for duplicates, and ensuring all references were formatted per IEEE standards, this phase also included these.

CHAPTER 4
RESULT, CONCLUSION AND FUTURE WORK

4.1 RESULT

The Review of the literature for this project yielded some significant fresh ideas on the field of neuro-symbolic artificial intelligence (NSAI). Analysing more than 20 high-impact research publications, we discovered significant trends, basic theories, architectural innovations, useful applications, main challenges, and fresh directions of research. The following sections go over the main findings together with their implications for NSAI's future.

4.1.1 Major Trends in NSAI Research

The study showed clearly a trend towards hybrid systems combining the symbolic reasoning capacity of conventional artificial intelligence with the adaptive learning capacity of neural networks. Modern NSAI systems originated in foundational works including "Logic Tensor Networks" (Serafini and Garcez, 2016) and "Neurosymbolic AI: The 3rd Wave" (Garcez and Lamb, 2020), which offered critical frameworks for combining logic and learning. Recent studies underlined in "Towards Cognitive AI Systems" (Wan et al., 2024) underline even more the need of architectures able to replicate human-like thinking by combining structured knowledge with data-driven learning.

4.1.2 Key Contributions to Foundational Theories

Many of the works significantly advanced NSAI's fundamental ideas. Early efforts on knowledge representation in expert systems by Hatzlygeroudis and Prentzas (2005) for example underlined the need of combining symbolic and neural methods to capture both structured knowledge and statistical patterns. More recent studies, including

“Bridging the Gap: Representation Spaces in Neuro-Symbolic AI” (Zhang and Sheng, 2024), proposed innovative approaches to produce unified representation spaces, so addressing a major field challenge.

4.1.3 Architectural Innovations and System Design

The literature mostly concentrated on architectural innovations; several papers offered fresh ideas for combining symbolic reasoning with neural learning. Notable examples with scalable, adaptable designs for demanding reasoning tasks are Logic Tensor Networks (Serafini and Garcez, 2016) and Neural-Symbolic VQA (Yi et al., 2019). These systems overrule the limitations of merely neural or symbolic approaches by offering a balanced approach that can control both exact logic and statistical learning. This section also covered specialised hardware for NSAI, as underlined in “Towards Efficient Neuro-Symbolic AI” (Wan et al., 2024), which underlined the demand of scalable, high-performance systems.

4.1.4 Real-World Applications and Impact

The study also highlighted NSAI’s growing impact in military systems, geoscience, healthcare, and autonomous robotics among other practical disciplines. Documents showing the practical benefits of hybrid systems in high-stakes, real-world settings included “Neuro-Symbolic AI for Military Applications” (Hagos and Rawat, 2024) and “Exploring Neuro-Symbolic AI Applications in Geoscience” (Chen et al., 2024). Similarly, “A Study on Neuro-Symbolic Artificial Intelligence: Healthcare Perspectives” (Hossain and Chen, 2025) discussed the critical role NSAI performs in increasing clinical decision support, tailored medicine, and diagnostic accuracy.

4.1.5 Challenges and Technical Barriers

Even with the tremendous progress in the field, several problems still arise including ethical concerns, interpretability, and scalability. Papers including “On the Relevance of Logic for AI" (Belle, 2024) and "Towards Efficient Neuro-Symbolic AI" (Wan et al., 2024) addressed issues stressing the need of more transparent, explainable AI systems able to manage complex, real-world data. Particularly scalability is still difficult since many NSAI systems require significant computational capacity to effectively combine neural learning and symbolic reasoning.

4.1.6 Future Directions and Emerging Trends

At last, the study revealed several fresh directions and trends for NSAI including the expansion of cognitive architectures and the integration of generative models. Papers "Unlocking the Potential of Generative AI through Neuro-Symbolic Architectures" (Bougzime et al., 2025) and "Towards Cognitive AI Systems" (Wan et al., 2024) underlined the possibility for producing more flexible, interpretable AI systems that could reason like humans using both symbolic knowledge and data-driven learning.

Overall, the literature review provided a comprehensive understanding of the current state of NSAI, highlighting its strengths, challenges, and future potential. This analysis will serve as a critical foundation for ongoing research and development in this rapidly evolving field.

4.2 CONCLUSION

Review of extensive material for this project produced acquired thorough and advanced knowledge of the fast expanding field of neuro-symbolic artificial intelligence (NSAI). By means of an analysis of more than 20 major papers covering basic ideas, architectural innovations, practical applications, critical challenges, and future directions, we developed a whole picture of NSAI's present situation and future possibilities.

This work presents insightful fresh ideas including the knowledge that NSAI represents a significant step towards artificial intelligence systems making decisions like those of humans. Emphasising the need of including symbolic logic with neural learning, basic works like "Neurosymbolic AI: The 3rd Wave" (Garcez and Lamb, 2020) and "Logic

Tensor Networks” (Serafini and Garcez, 2016) so supplied the theoretical framework for modern NSAI systems. These experiments revealed that hybrid approaches surpass the boundaries of either fully neural or symbolic systems by offering more interpretable, scalable, and efficient solutions for demanding reasoning tasks.

The study also underlined the significance of architectural innovations since papers like ”Neural-Symbolic VQA” (Yi et al., 2019) present fresh ways for combining perception and reasoning. From visual question answering to autonomous decision-making and cognitive computing, these systems have considerably broad the range of activities NSAI systems can undertake.

Two actual NSAI implementations that highlight even more the pragmatic relevance of this technologies are those underlined in “Neuro-Symbolic AI in Healthcare” (Hossain and Chen, 2025) and “Neuro-Symbolic AI for Military Applications” (Hagos and Rawat, 2024). These tests showed that NSAI can significantly raise performance in high-stakes, real-world environments including military operations, healthcare diagnostics, and scientific discovery by combining the interpretability of symbolic logic with the flexibility of neural networks.

Still, the study also pointed up some rather significant problems that must be addressed if NSAI is to really come to terms with herself. Underlined the need of scalable, interpretable designs that might control the complexity of real-world data while preserving openness and responsibility were papers “Towards Cognitive AI Systems” (Wan et al., 2024) and “On the Relevance of Logic for AI”. As discussed in “Towards Efficient Neuro-Symbolic AI” (Wan et al., 2024), the research also underlined the ongoing demand of specialist hardware to support the computational needs o” NSAI systems.

Not least of all, at last the paper “Unlocking the Potential of Generative AI through Neuro-Symbolic Architectures” (Bougzime et al., 2025) at last addressed some fascinating future directions for NSAI including the integration of generative models and cognitive architectures. These new trends suggest that NSAI will stay indispensable in the development of next-generation artificial intelligence systems able of human-like thinking, learning, and decision-making.

Emphasising NSAI's achievements as well as its ongoing challenges, this project presents the current state of affairs. The knowledge gained in this review will be much appreciated in future studies guiding the evolution of ever more complex, interpretable, and scalable artificial intelligence systems in the next years.

4.3 FUTURE WORK

Although the present state of Neuro-Symbolic AI (NSAI) has been fully discussed in this literature review, the field is still in its early years and presents excellent opportunities for more research and development. Based on this research, several fascinating paths have emerged that might offer NSAI systems modern tools and help to solve present issues.

4.3.1 Scalable and Efficient Architectures

One of the most significant challenges identified in this review is the need of scalable, high-performance systems able to efficiently mix symbolic reasoning with neural learning. Documents such "Towards Efficient Neuro-Symbolic AI" (Wan et al., 2024) underlined the need of particularised hardware for NSAI, including hybrid computing architectures and neuromorphic chips and hybrid hardware. Future research should mostly focus on optimising these architectures for low latency, high scalability, and real-time performance so NSAI systems may manage demanding, real-world data at scale.

4.3.2 Improved Representation Spaces

Integration of symbolic and neural data remains a main technical obstacle for NSAI systems. Original ideas for consistent representation spaces even if great challenges still exist were offered in publications such as "Bridging the Gap: Representation Spaces in Neuro-Symbolic AI" (Zhang and Sheng, 2024). NSAI systems will become more interpretable and raise their reasoning capacity if more flexible context-aware representation spaces able to capture both structured knowledge and statistical patterns develop.

4.3.3 Enhanced Interpretability and Explainability

Transparency and open artificial intelligence systems still provide a great challenge for NSAI, as underlined in "On the Relevance of Logic for AI" (Belle, 2024). Future research should focus on creating hybrid systems that can exactly support their design choices, so promoting confidence and responsibility in high-stakes projects including military systems, driverless cars, and healthcare.

4.3.4 Advanced Cognitive Architectures

Papers "Towards Cognitive AI Systems" (Wan et al., 2024) and "Neurosymbolic AI: The 3rd Wave" (Garcez and Lamb, 2020) underlined the possibility for creating cognitive architectures reflecting human-like thinking. Future research should focus on building architectures that can mix perception, reasoning, and decision-making in a single framework so that artificial intelligence systems may grasp and reason about the surroundings in a more human-like way.

4.3.5 Integration with Generative Models

Documents including "Unlocking the Potential of Generative AI by Neuro-Symbolic Architectures" (Bougzime et al., 2025) underlined underlined the prospects for combining generative models with NSAI systems to raise scalability, flexibility, and creativity. Future studies should look at the possibility of combining generative models with symbolic thinking to create hybrid systems able to generate complex outputs while preserving control and openness.

4.3.6 Domain-Specific Applications and Real-World Impact

The study also found several fascinating NSAI applications in geoscience (Chen et al., 2024), military systems (Hagos and Rawat, 2024), healthcare (Hossain and Chen, 2025). Future research should focus on building domain-specific NSAI systems able to use domain knowledge for better performance and dependability in practical environments.

4.3.7 Ethical and Social Considerations

Ethical issues will become more important as NSAI systems gain acceptance. Books such "On the Relevance of Logic for AI" (Belle, 2024) underlined the need of honest, open, responsible AI systems able to be relied upon in highly stakes surroundings. Future research should mostly focus on development of moral rules, best practices, and legal systems for responsible and safe NSAI operation.

4.3.8 Long-Term Generalization and Transfer Learning

Research on the opportunities for long-term generalisation and transfer learning in NSAI systems ought eventually to take front stage. As noted in papers including "Towards Cognitive AI Systems" (Wan et al., 2024), this includes designing buildings that can quickly adapt to new tasks, transfer knowledge across sectors, and learn from limited data.

Future prospects abound in NSAI that will allow the creation of more solid, interpretable, scalable artificial intelligence systems able to really understand and reason about the environment. Overcoming challenges and extending on the basic work covered in this review will enable next generation of intelligent systems to be produced and NSAI fully exploited by future researchers.

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