Neuro-Symbolic AI for Advanced Signal and Image Processing: A Review of Recent Trends and Future Directions

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***Abstract*—Neuro-Symbolic Artificial Intelligence (NSAI) is an emerging paradigm that combines neural networks with symbolic reasoning. This paper provides a comprehensive review of NSAI techniques and their applications in advanced signal and image processing. The paper begins by introducing the fundamentals of NSAI and highlighting how it bridges the gap between data-driven learning and knowledge-based reasoning. It then surveys several key application domains, such as biomedical, autonomous robotics, and IoT, in order to understand the benefits and challenges of that integration. For each domain, how NSAI methods improve upon traditional purely neural or purely symbolic approaches is illustrated. A comparative analysis with conventional AI techniques is presented, underscoring the advantages of NSAI in terms of interpretability, generalization, and flexibility. The challenges that arise in developing NSAI systems, such as computational complexity, integration of heterogeneous models, and ethical considerations, are also discussed. Finally, future research trends in NSAI for signal and image processing, as well as the path toward more explainable and generalizable AI, are synthesized.**

***Index Terms*—Neuro-Symbolic AI; Signal Processing; Image Processing; Explainable AI.**

I. Introduction

NSAI represents a promising frontier in artificial intelligence by integrating the strengths of neural networks and symbolic reasoning to address complex problems that neither approach can solve alone. Neural networks excel in pattern recognition and have achieved significant success in domains such as image and speech processing, but they often lack explainability and explicit reasoning capabilities, operating as “black boxes” [1], [2]. Symbolic AI, on the other hand, is inherently interpretable and excels in logical reasoning but struggles with perception from raw data and requires extensive manual knowledge engineering [2]. NSAI seeks to bridge these gaps by combining the robust statistical learning of neural networks with the structured knowledge and logic of symbolic AI, enabling systems to reason, make decisions, and generalize knowledge from large datasets more effectively [3], [4]. Recent advancements in NSAI have demonstrated its potential in various applications, such as enhancing the reliability of AI in the Internet of Things (AIoT) by addressing challenges related to testability, verifiability, and interpretability [4]. Moreover, NSAI approaches have shown significant improvements in tasks like question answering and image classification, outperforming traditional neural models [5], [6]. The integration of symbolic reasoning with neural networks also enhances natural language processing capabilities, providing nuanced understanding and contextually relevant responses, as seen in applications like Named Entity Recognition [7]. Despite its potential, NSAI is still in its early stages and not widely adopted by practitioners, highlighting the need for further research and development to establish a unifying theory and address challenges such as scalability and ethical considerations [3], [6], [8].

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NSAI represents a promising approach to overcoming the limitations of traditional AI systems in advanced signal and image processing tasks, which require both low-level sensory interpretation and high-level reasoning. Traditional AI systems, particularly those relying solely on deep neural networks, often excel in pattern recognition but struggle with incorporating commonsense constraints and are prone to brittleness when faced with scenarios outside their training distribution [9], [10]. Conversely, purely symbolic systems lack the capability to handle the complexity and variability of real-world sensory data [10]. NSAI offers a hybrid model that integrates neural networks with symbolic reasoning, thereby enhancing interpretability, robustness, and trustworthiness while facilitating learning from less data [10].

In this paper, a structured overview of NSAI for advanced signal and image processing is presented. Section II explains the methods used for this survey. Section III introduces the basics of NSAI, explaining core concepts and paradigms of neural-symbolic integration. Section IV surveys several application areas where NSAI has been applied, including biomedical, robotics, multimedia, audio technologies, etc. Examples in each area are provided to illustrate the benefits of the neuro-symbolic approach. In Section V, ongoing challenges in NSAI development—computational challenges, integration difficulties, and ethical considerations are discussed. Section VI then explores future trends and potential directions for research in neuro-symbolic AI, and finally Section VII concludes the paper.

II. Methods

This survey was conducted through a structured and replicable methodology designed to capture the most relevant and up-to-date literature on NSAI in signal and image processing. The process involved systematic keyword-based searches across multiple databases, the application of inclusion and exclusion criteria to filter results, and the synthesis of findings across different application domains.

The literature search was carried out using a combination of academic databases and search engines, including Google Scholar, IEEE Xplore, SpringerLink, and arXiv. These platforms were selected to ensure broad coverage of both peer-reviewed and preprint publications. The search strategy involved using combinations of keywords such as “neuro-symbolic AI,” “hybrid AI,” “logical neural networks,” “neuro-symbolic integration,” “explainable AI,” “symbolic reasoning,” “signal processing,” “image processing,” and “NSAI architecture.”

To ensure the relevance and quality of the reviewed studies, specific inclusion and exclusion criteria were applied. Articles were included if they were published between 2018 and 2025, focused on neuro-symbolic AI techniques, even if not explicitly referred to as ”Neuro-symbolic”, and discussed their application to domains related to signal or image processing. Preference was given to works that included architectural contributions, comparative evaluations against neural or symbolic baselines, NSAI applications in signal or image processing, or insights into interpretability, scalability, or robustness. Application domains considered included biomedical systems, robotics, IoT, industrial monitoring, multimedia, geospatial analysis, and audio or speech technologies.

Studies were excluded if they were not written in English, did not include any symbolic reasoning or neural network component, or lacked direct application to signal or image processing tasks.

Following the initial screening, selected papers were reviewed in detail. The final list considers a total of 105 references, which are grouped by year of publication. A temporal analysis of the selected publications reveals a significant surge in research interest in neuro-symbolic AI, particularly in signal and image processing applications. As shown in Figure 1, there has been a sharp increase in publications between 2022 and 2025, with over 65 papers appearing in the 2024–2025 interval alone. This trend indicates a growing academic and industrial focus on the integration of neural and symbolic paradigms, reflecting both technological maturity and heightened demand for interpretable, robust AI solutions in complex domains.

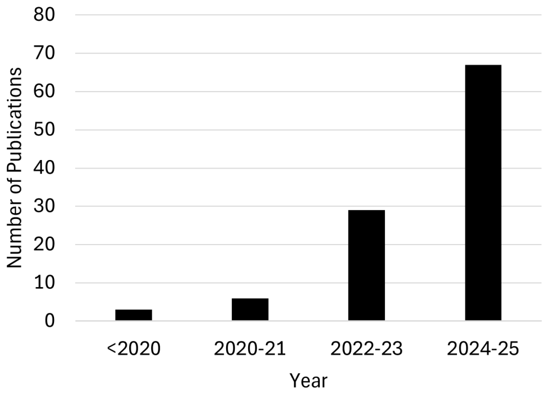

Fig. 1. Distribution of publications related to neuro-symbolic AI in signal and image processing across time intervals.

III. Neuro-Symbolic AI

Neuro-symbolic AI represents a promising fusion of neural networks and symbolic logic, drawing inspiration from the human brain’s processing capabilities to enhance AI systems’ learning and reasoning abilities. The ”neuro” component leverages neural networks to emulate the brain’s ability to learn from data and adapt to new information, akin to neuroplasticity, which allows for continuous learning and adaptation without catastrophic forgetting [11]. This approach is complemented by the ”symbolic” component, which employs logical reasoning and symbolic representations to facilitate tasks such as decision-making and knowledge representation, enabling AI to process ”if-then” statements and represent knowledge in human-understandable forms [12], [13]. The integration of these components addresses the limitations of purely neural or symbolic systems, as neuro-symbolic AI can outperform models that rely solely on one approach [3]. Despite its potential, challenges remain, particularly in achieving explainability and transparency, which are crucial for the broader adoption of neuro-symbolic systems [14]. Additionally, the field is exploring the application of neuro-symbolic AI in various domains, such as autonomous communication systems, where it enhances signal processing and security through adaptive decision-making and pattern recognition [15]. The development of brain-inspired cognitive architectures further supports this integration, offering insights into how AI can emulate human-like intelligence in complex tasks like perception and reasoning [16], [17].

A. The different NSAI Architectures

Figure 2 represents the different NSAI types/architectures, which are now detailed. These types are according to [18]. Their differences rely mostly on the connection between the neural architecture and the symbolic architecture, except for type 6.

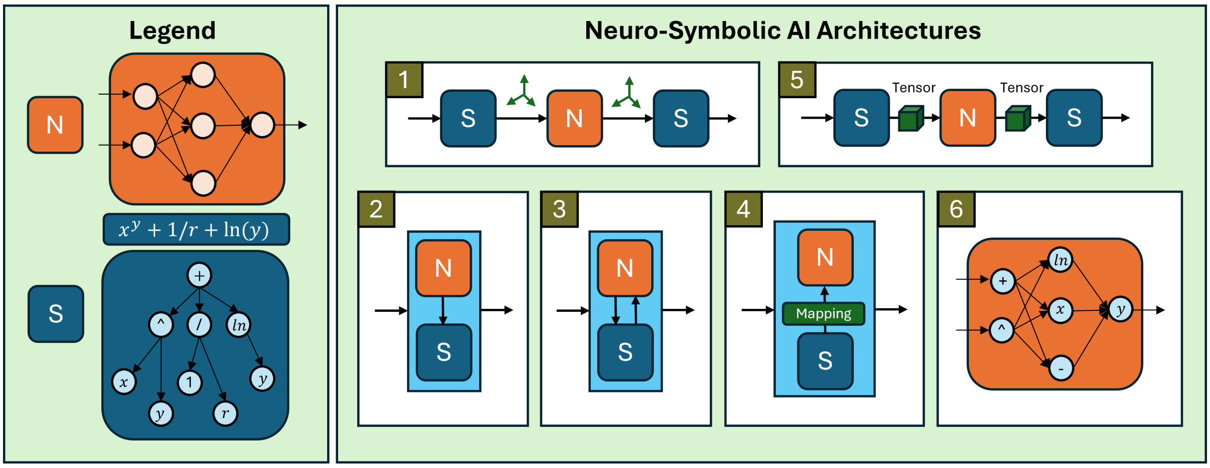

Fig. 2. Neuro-Symbolic AI types, according to [18].

The Type 1, the Symbolic Wrapper architecture, which integrates symbolic systems with neural networks, is a compelling approach in neuro-symbolic AI, allowing symbolic reasoning to guide both input and output phases while leveraging neural networks for data-driven learning. This design is exemplified by systems like DeepProbLog, a probabilistic logic programming framework that integrates deep learning through neural predicates. DeepProbLog enables end-to-end training by combining symbolic and subsymbolic representations, allowing for program induction, probabilistic logic reasoning, and learning from raw examples [19]. Similarly, ProbLog combined with Convolutional Neural Networks (CNNs) serves as a foundational example of this architecture, where the symbolic ProbLog system invokes CNNs to handle perceptual tasks while retaining overall symbolic interpretability and robustness in decision-making [19]. Another well-known instance is the Neuro-Symbolic Concept Learner (NSCL), which uses symbolic programs to orchestrate the behavior of neural modules in visual question answering. In NSCL, symbolic reasoning guides the neural perception pipeline, enabling the model to interpret complex visual scenes and execute queries with a high level of generalization and transparency [20]. Similarly, Visual Question Answering (VQA) systems with symbolic program execution rely on symbolic planners to generate interpretable program structures that are then executed over neural-perceptual representations of images, resulting in more accurate and explainable answers to visual queries [21]. Neuro-symbolic Inductive Learning (NSIL) also fits within this paradigm, [22] as well as hybrid neuro-symbolic robotics, symbolic reasoning systems that encapsulate neural perception modules to enable intelligent agents—such as robots—to combine high-level symbolic planning with low-level visual or sensory processing, allowing them to execute complex, grounded tasks [23].

NSAI Type 2, or Symbolic [Neuro] (S[N]), where symbolic systems dominate, and neural modules are used internally, are less common in modern frameworks but still hold significant potential in specific applications. These systems leverage the strengths of symbolic reasoning for high-level decision-making and neural networks for perception and pattern recognition. For instance, in autonomous communication systems, a neuro-symbolic AI framework integrates CNNs for signal feature extraction with symbolic AI for rule-based adaptation, achieving substantial improvements in signal-to-noise ratio and bit error rate, demonstrating the effectiveness of combining neural and symbolic components for real-time, adaptive communication protocols [15]. Similarly, in scene interpretation, the NeuroScene framework uses neural networks for feature extraction and symbolic AI for reasoning, effectively interpreting complex visual scenes and providing interpretable answers, which is crucial for applications requiring detailed scene understanding [24]. Moreover, the NSP framework for path planning from natural language inputs exemplifies the integration of neural reasoning with symbolic path planning, achieving high accuracy and efficiency in generating valid paths [25]. Despite their potential, these systems face challenges such as inefficiencies on standard hardware due to the memory-bound nature of vector-symbolic operations and complex flow control, necessitating cross-layer optimization solutions to improve performance and scalability [10]. Additionally, frameworks like NeSyCoCo address challenges in compositional generalization by mapping symbolic representations to differentiable neural computations, enhancing adaptability and performance in vision-language reasoning tasks [26].

Type 3 neuro-symbolic AI systems, characterized by their tight bidirectional interaction between neural and symbolic components, represent a significant advancement in AI, particularly in domains requiring both low-level perception and high-level planning. These systems enable a cooperative relationship where neural models adjust outputs based on symbolic constraints, and symbolic modules evolve reasoning based on neural feedback. This integration is particularly powerful in fields like robotics, where a neural vision system processes the environment while a symbolic planner determines actions, facilitating continuous influence between both layers [23], [27]. AlphaGo and AlphaZero exemplify such systems, where neural networks are used for pattern recognition and symbolic reasoning for strategic decision-making, demonstrating the potential of neuro-symbolic reinforcement learning (NS-RL) in complex environments [28]. The LogiCity platform further illustrates the application of neuro-symbolic systems in multi-agent settings, allowing for dynamic interaction and adaptation in urban environments [29], [30]. NeSyA, a temporal neuro-symbolic architecture, addresses the challenge of reasoning over sequences of subsymbolic observations, showcasing improved scalability and performance in temporal tasks [13]. The integration of Probabilistic Soft Logic (PSL) with deep learning, where symbolic loss guides neural learning during execution, exemplifies the synergy between symbolic reasoning and neural adaptation, enhancing learning efficiency and interpretability [5]. These systems collectively demonstrate the promise of neuro-symbolic AI in achieving more robust, interpretable, and adaptable artificial intelligence, addressing challenges such as reasoning, generalization, and transferability across domains [31], [32].

Type 4 neuro-symbolic AI architectures, which establish a sequential connection between neural networks and symbolic systems through an explicit mapping layer, are pivotal in converting continuous neural outputs into structured symbolic knowledge. This conversion is crucial for tasks such as knowledge extraction from unstructured data and translating visual features into scene graphs. Neural Symbolic Machines (NSM) exemplify this by combining a neural "programmer" with a symbolic "computer" to map language utterances to executable programs, leveraging a Lisp interpreter for program execution and optimization through REINFORCE, achieving state-of-the-art results in semantic parsing tasks like WebQuestionsSP without extensive feature engineering [33], [34]. Similarly, the Neural-Symbolic Recursive Machine (NSR) employs a Grounded Symbol System to achieve systematic generalization across domains by integrating neural perception with symbolic reasoning, demonstrating superior performance in tasks such as SCAN and PCFG due to its symbolic representation and inductive biases [35]. The *seq2grid* module offers another perspective by transforming input sequences into grids, enabling neural networks to generalize out-of-distribution on symbolic reasoning tasks, thus enhancing models like TextCNN for tasks such as bAbI QA without external memory [36]. Furthermore, Tensor Product Representations (TPRs) in the TP-N2F framework encode natural language into structured symbolic forms, outperforming traditional seq2seq models by explicitly capturing symbolic structures, thereby enhancing interpretability and performance in formal-language problem-solving [37]. Graph-based Symbolically Synthesized Neural Networks (G-SSNNs) introduce symbolic features into neural modules, modulating data efficiency and generalization, and providing insights into symbolic program semantics without manual engineering [38], [39].

Type 5 neuro-symbolic AI architectures, which embed symbolic information directly into tensor representations, are a promising approach to enhancing the reasoning capabilities of neural networks by integrating symbolic knowledge in a differentiable manner. This integration is achieved through various methods such as embedding layers, graph-based encodings, and soft constraints in the loss function, allowing neural networks to learn representations that align with symbolic structures. Logic Tensor Networks (LTNs) exemplify this approach by embedding symbolic knowledge into tensors and loss functions, enabling the learning of logical axioms through differentiable operators. LTNs utilize fuzzy logic to handle continuous truth values, facilitating the optimization of neural models to satisfy a knowledge base of logical formulas [40], [41], [42]. The PROTOtypical Logic Tensor Networks (PROTO-LTN) extend LTNs by introducing a common predicate for class membership, reducing parameter complexity and enhancing zero-shot learning capabilities by grounding abstract concepts as class prototypes in a high-dimensional space [42], [43]. Semantic loss functions, as discussed in the context of Human Activity Recognition (HAR), further illustrate the potential of tensor-based symbolic encoding by infusing knowledge constraints into the training phase, thus avoiding the need for symbolic reasoning during classification and improving model performance on real-world datasets [44], [45]. KENN (Knowledge-Enhanced Neural Network) also leverages tensor-based symbolic encoding by incorporating logical clauses into neural networks, enhancing performance in multi-label classification tasks through the inclusion of learnable clause weights [46]. These approaches demonstrate the versatility and effectiveness of tensor-based symbolic encoding in various applications, from zero-shot learning to structured prediction, by integrating symbolic knowledge into the neural network training process, thereby improving both interpretability and generalization capabilities [42], [44], [46].

Type 6 neuro-symbolic AI architectures represent a deeply integrated approach where symbolic structures are directly processed by neural networks, allowing for a seamless blend of symbolic reasoning and neural computation. Neural Theorem Provers (NTP) and Neural Symbolic Execution (NSE) are examples of systems that integrate symbolic reasoning with neural networks, allowing for the processing of complex symbolic structures. Graph Neural Networks (GNNs) are particularly effective for handling logic graphs, as they can model relationships and dependencies within the data, enabling more sophisticated reasoning over symbolic inputs [47]. SymbolNet, a neural network approach to symbolic regression, demonstrates the potential of neural networks to handle high-dimensional symbolic data efficiently, using dynamic pruning to optimize both training loss and expression complexity [48], [49]. Similarly, Graph-based Symbolically Synthesized Neural Networks (G-SSNNs) leverage symbolic programs to enhance data efficiency and generalization, showing that the integration of symbolic features can modulate neural network performance [38], [39]. In the realm of solving mathematical problems, a neuro-symbolic method has been developed to solve differential and functional equations, producing symbolic expressions that are both interpretable and adaptable to various tasks [50]. Furthermore, spiking neural networks have been explored for reasoning over symbolic structures like knowledge graphs, utilizing graph embedding paradigms and error backpropagation to encode symbolic and multi-relational information [51], [52]. These developments show how the symbolic and neural paradigms are increasingly working together, and they present encouraging paths towards creating interpretable and sophisticated AI systems that can reason across a variety of fields.

IV. Applications of NSAI in Signal and Image Processing

Figure 3 is a summary of all the signal and image processing application categories where NSAI has the potential of being applied. This section is split into different subsections, each corresponding to a different application category. These categories include: Communications and Information Theory; Biomedical and Healthcare; Autonomous Systems and Robotics; Industrial Monitoring and IoT; Multimedia; Vision and Entertainment; Remote Sensing and Geospatial; and Audio and Speech Technologies.

A. Communications and Information Theory

In recent developments, a novel neuro-symbolic AI framework has been introduced to facilitate real-time self-evolving signal processing in autonomous communication systems. This system seamlessly integrates multi-scale convolutional neural networks (CNNs) for hierarchical signal feature extraction with symbolic AI mechanisms for rule-based adaptation. The result is a framework capable of autonomously optimizing communication protocols without human intervention. Empirical results show a 33% improvement in signal-to-noise ratio (SNR) and a 44% reduction in bit error rate (BER) compared to existing communication models [15]. Furthermore, the incorporation of quantum key distribution (QKD) enhances the security of dynamically evolving communication channels, making the system robust and secure in highly variable environments.

In parallel, significant progress has been made in near-sensor neuro-symbolic AI computing using silicon photonics. The proposed Neuro-Photonix system enables neural dynamic computations directly on analog data through photonic devices, which naturally support granularity-controllable convolution operations. This approach drastically reduces the energy and latency involved in the conversion, transmission, and processing of sensory data. Achieving 30 GOPS/W, the system demonstrates a 20.8-fold reduction in power consumption when compared to standard ASIC-based solutions. Additionally, it supports the generation of HyperDimensional (HD) vectors for symbolic AI tasks, establishing it as a cost-effective and efficient solution particularly suited for Internet of Things (IoT) sensor nodes [53].

Another pioneering effort involves neuro-symbolic causal reasoning in semantic communications through an emergent semantic communication (ESC) framework. This system integrates neuro-symbolic AI with causal reasoning to enhance the reliability of communication channels while simultaneously reducing the amount of data transmitted. Utilizing a signaling game paradigm, it facilitates the co-design of transmission and reception strategies that converge to a local equilibrium. This process results in the emergence of a compact and efficient transmit vocabulary that supports logical reasoning and generalization to novel scenarios. Moreover, the fusion of generative flow networks (GFlowNets) with logical neural networks further strengthens the ESC framework, offering improved semantic reliability and reduced transmission loads in comparison to conventional systems [54].

B. Biomedical and Healthcare

Recent advances in biomedical and healthcare AI systems have led to the development of hybrid neuro-symbolic frameworks that integrate neural learning with symbolic reasoning to enhance transparency, interpretability, and diagnostic performance.

In the study "Explainable Diagnosis Prediction through Neuro-Symbolic Integration," the authors propose a hybrid model using logical neural networks (LNNs) that combine learnable parameters with logical operators such as conjunction and disjunction. These neural units process input features such as age, blood pressure, and gender to estimate diagnosis probabilities, while symbolic rules derived from domain knowledge provide logical constraints and interpretability for the predictions [55].

The "MediSage" system presents a general-purpose AI assistant for healthcare that merges neural processing of electronic health records (EHRs) with symbolic reasoning over a structured knowledge graph. Neural

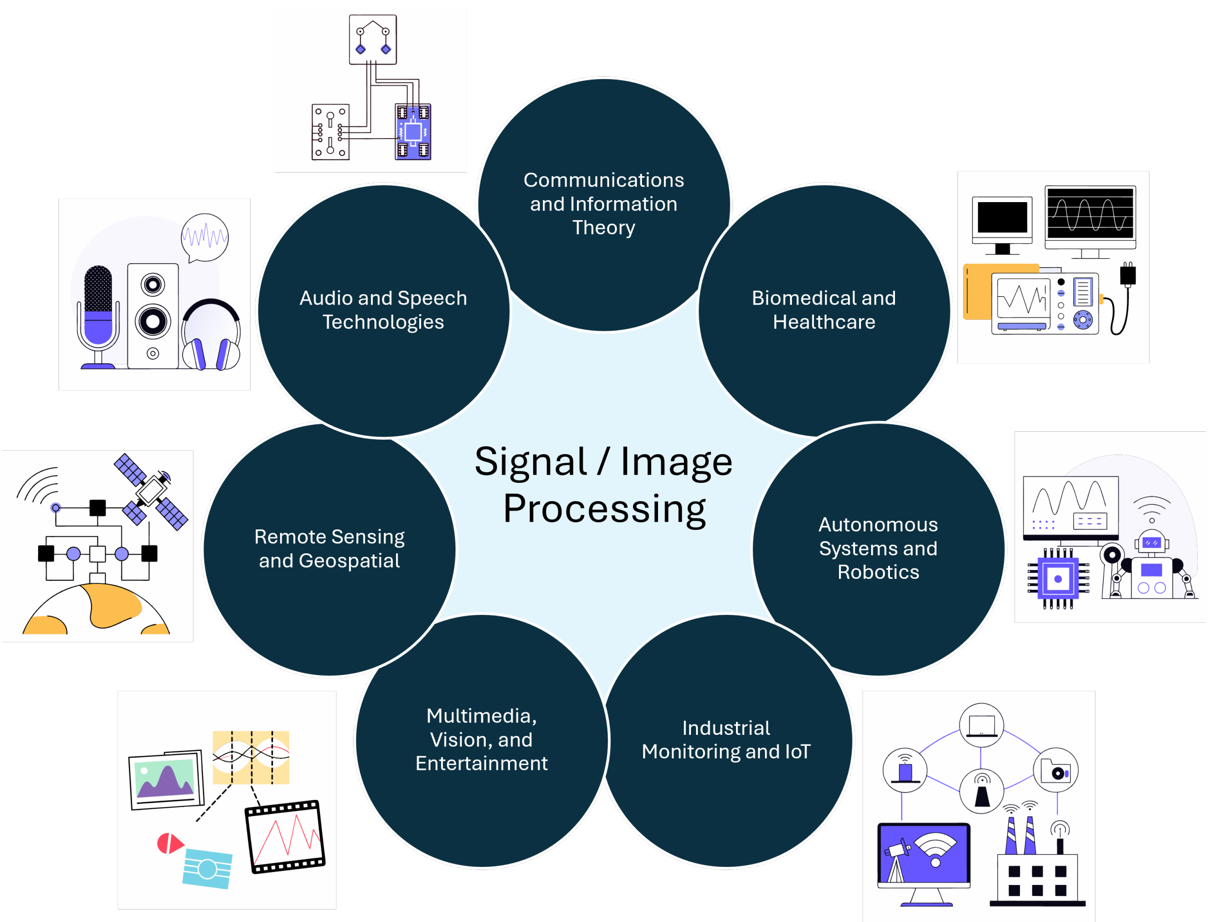

Fig. 3. Signal and Image Processing Engineering Applications of AI

TABLE I
COMPARISON OF NEURAL AND SYMBOLIC UNITS ACROSS FRAMEWORKS

Framework	Neural Units	Symbolic Units	Integration Insight
Self-Evolving Signal Processing [15]	Multi-scale CNNs for real-time signal pattern recognition.	Rule-based symbolic AI for adaptive protocol optimization.	Combines learned features and logical rules for self-evolving, secure communication.
Neuro-Photonix (Silicon Photonics) [53]	Photonic DNNs with multi-resonator systems for analog convolution.	HyperDimensional Computing for symbolic encoding and reasoning.	Enables low-latency, energy-efficient processing suitable for IoT nodes.
Emergent Semantic Communication (ESC) [54]	GFlowNets for causal reasoning and learning communication strategies.	Logical neural networks for symbolic formula evaluation.	Creates a reasoning-aware emergent vocabulary with reduced transmission load.

models extract complex patterns from patient data, while the symbolic units provide step-by-step explanations using integrated clinical knowledge, enhancing trust and transparency in medical recommendations [56].

A similar approach is taken by Wang et al., where pre-trained computer vision models perform initial image feature extraction, and symbolic inductive logic learning (ILL) creates disjunctive logical rules for label assignment. This system demonstrates effective human-AI collaboration, achieving high labeling accuracy even with limited labeled data [57].

The integration of deep learning models with symbolic explainability tools addresses the need for clinical transparency [58]. Neural models support diagnostic prediction in fields such as radiology and oncology, while symbolic systems like rule-based engines and knowledge graphs allow clinicians to understand the decision-making processes

The use of deep learning for tumor detection and segmentation is highlighted by Yousefirizi et al., paired with symbolic radiomics and handcrafted feature extraction to ensure that AI predictions remain interpretable and clinically valid [59].

The ”MARS” system introduces a neurosymbolic framework for drug discovery by integrating neural networks that predict drug mechanisms of action with symbolic logical rules and a knowledge graph (MoA-net). The symbolic component supports biological alignment and interpretability of neural outputs, aiding researchers in understanding complex drug interactions [60].

C. Autonomous Systems and Robotics

Recent advances in autonomous systems and robotics have shown that neuro-symbolic integration can significantly improve the flexibility, interpretability, and efficiency of decision-making and perception in complex environments.

The DeepSym framework introduces a hybrid encoder-decoder model with a binary bottleneck layer, which learns action-grounded object and effect categories from unsupervised robot interaction. The latent binary representations are interpreted using decision trees to extract symbolic rules in the Probabilistic Planning Domain Definition Language (PPDDL), enabling robust symbolic planning and task execution. This approach allows robots to autonomously discover discrete symbols and relational rules from raw interaction data, facilitating manipulation and general planning in both robotic and abstract domains [61].

Another general-purpose framework for neuro-symbolic integration in autonomous robotics proposes the use of neural networks for processing perceptual data (e.g., object recognition, sensory analysis), while symbolic modules handle decision-making by applying structured rules to the processed data. This separation of concerns enhances context-awareness and enables interpretable, logic-based reasoning to guide robot behavior in dynamic environments [23].

In the NEUSIS framework, developed for UAV search missions, neural units handle real-time visual perception and entity detection in complex terrains, while symbolic reasoning modules maintain a probabilistic world model to inform high-level planning and goal management. This compositional integration results in superior localization accuracy and mission success rates in hazard-prone environments, as demonstrated in simulated urban search missions [62].

The AnyNav framework focuses on off-road navigation by combining neural networks for visual friction estimation with symbolic reasoning over physical terrain models. Neural modules process visual inputs to infer terrain friction coefficients, which are used by symbolic modules to apply physical laws and ensure realistic and safe navigation decisions [63].

Lastly, the approach by Tziafas and Kasaei applies neuro-symbolic methods to enhance interpretability in robot manipulation. Neural networks perform visual grounding and object detection, while symbolic reasoning supports logic-based task execution such as counting and spatial relation understanding. This leads to more robust user interaction and generalization in manipulation tasks [64].

D. Industrial Monitoring and IoT

Neuro-symbolic integration is increasingly being applied to industrial monitoring and Internet of Things (IoT) applications, where it supports enhanced anomaly detection, semantic reasoning, and energy-efficient processing. These hybrid systems combine the pattern recognition capabilities of neural networks with the interpretability and domain knowledge of symbolic AI, enabling real-time, context-aware decision-making in complex industrial environments.

In the work by Capogrosso et al., neural units are implemented through diffusion-based models that perform real-time anomaly detection in Industry 4.0 environments. These models process large volumes of manufacturing data to identify irregularities. The symbolic layer consists of industrial ontologies that provide structured domain knowledge, allowing for improved accuracy and context awareness during anomaly detection [65], [66], [67].

Burghouts et al. propose a neuro-symbolic system that uses language-vision models as neural units to extract probabilistic object proposals from industrial images. Symbolic reasoning is applied via first-order logic, which defines spatial relationships between objects. This enables open-world visual reasoning to detect situations such as abandoned tools or equipment leaks in complex industrial settings [68].

Curry et al. describe a multimodal event processing system where deep neural networks handle computer vision, audio, and linguistic streams. Symbolic event processing rules interpret semantic and temporal content, enabling the expression of complex event patterns. The system processes video input at 30 fps with subsecond latency and achieves a 127-fold latency improvement using content-aware load-shedding techniques, while preserving accuracy [69].

In Bosch's application, Lu et al. integrate neural networks for machine learning on manufacturing data with symbolic ontologies for semantic modeling of industrial assets. This hybrid approach allows for semantic data integration and uniform data representation, which improves interoperability and supports intelligent decision-making across heterogeneous industrial systems [4].

Lee et al. present the NSHD framework, which combines convolutional neural networks (CNNs) for visual data processing with hyperdimensional computing as a symbolic layer. HD computing, inspired by human memory, allows for interpretable symbolic learning. The framework achieves up to 64% energy savings compared to CNNs alone, while maintaining high accuracy [70].

TABLE II
COMPARISON OF NEURAL AND SYMBOLIC UNITS IN BIOMEDICAL AND HEALTHCARE APPLICATIONS

System / Paper	Neural Units	Symbolic Units	Integration Insight
Diagnosis Prediction [55]	Logical neural networks with differentiable logic operators for binary classification.	Domain-specific logical rules to improve interpretability and transparency.	Enhances explainability in diagnosis through interpretable logic.
MediSage [56]	Neural models trained on EHR and knowledge graphs to generate personalized recommendations.	Clinical knowledge graph enables symbolic reasoning and rationale explanation.	Combines learning and reasoning for healthcare assistant functionality.
Rapid Image Labeling [57]	Pre-trained CV models for feature extraction and initial prediction.	Inductive logic learning generates logic rules for image annotation.	Achieves efficient labeling and human-AI collaboration.
XAI in Healthcare [58]	Deep learning for EHR and image processing across specialties.	Rule-based explainable models and knowledge graphs.	Improves clinical decision-making by increasing transparency.
Medical Imaging [59]	CNNs for image classification, segmentation, and prognosis.	Radiomics with handcrafted features and rule-based systems.	Balances diagnostic accuracy with model interpretability.
MARS [60]	Neural networks with learned rule weights for drug discovery.	Logical rules and biological knowledge graph (MoA-net).	Supports mechanism of action interpretation and drug relation analysis.

TABLE III
COMPARISON OF NEURO-SYMBOLIC FRAMEWORKS IN AUTONOMOUS SYSTEMS AND ROBOTICS

Framework	Neural Units	Symbolic Units	Integration Insight
DeepSym [61]	Encoder-decoder with binary bottleneck; convolutional encoder and MLP decoder.	Decision tree extracts symbolic rules in PPDDL for planning.	Learns discrete symbols from interaction data for autonomous manipulation and planning.
Neuro-Symbolic Robotics [23]	Deep learning for sensory interpretation and pattern recognition.	Rule-based symbolic reasoning for decision-making.	Enables context-aware behavior via structured perception-to-reasoning pipeline.
NEUSIS [62]	Vision models for UAV perception and EOI detection.	Probabilistic world model and symbolic planners.	Improves UAV mission planning with reasoning over uncertain environments.
AnyNav [63]	Visual models estimate terrain friction from off-road images.	Symbolic physical modeling for path planning.	Fuses perception with physical logic to ensure safe, interpretable navigation.
Tziafas and Kasaei [64]	Neural vision for object grounding and spatial detection.	Logic modules for spatial reasoning and counting.	Improves interpretability and task grounding in robot manipulation.

E. Multimedia, Vision, and Entertainment

The integration of neural and symbolic AI in multimedia, vision, and entertainment applications enables systems to combine the perceptual strength of deep learning with structured reasoning over visual content. This hybrid approach supports scene understanding, video interpretation, and generative visual tasks with enhanced flexibility and interpretability.

Ritchie et al. explore neurosymbolic models in computer graphics, where neural units serve multiple purposes, including pattern learning from visual data, guiding program synthesis, and acting as neural primitives within domain-specific languages (DSLs). These units are responsible for refining procedural models or generating visual content from constraints. Symbolic units, on the other hand, represent structured programs that define visual elements and execution logic. The framework relies on symbolic DSLs to encode interpretable and manipulable visual programs [71].

In the LASER framework, presented by Huang et al., neural units extract fine-grained spatial and temporal video features using pretrained visual encoders. These features are learned with contrastive and semantic losses to align with high-level specifications. Symbolic units define spatio-temporal logic constraints and construct scene graphs to represent evolving visual entities and their relationships. The system aligns raw video clips with propositional logic specifications, significantly improving semantic video understanding and achieving high F1-scores across complex predicate evaluations [72].

The pix2rule model by Cingillioglu et al. features neural networks for low-level image perception, performing object recognition and feature extraction. The symbolic module translates this data into symbolic rules for high-level reasoning. This combination allows the system to learn rules from visual input and apply abstract logic to image-based tasks [73].

Kim et al. propose NeuroScene, which integrates a ResNet and Mask R-CNN as neural units to extract image features and segment regions of interest. Symbolic units then interpret this visual content through semantic parsing and logic-based reasoning. This enables users to query the visual scene using natural language, with symbolic programs translating queries into scene graph operations [24].

Lastly, the Neuro-Symbolic Video Search system by Choi et al. separates semantic perception and temporal reasoning. Neural units, based on vision-language

TABLE IV
COMPARISON OF NEURO-SYMBOLIC FRAMEWORKS IN INDUSTRIAL MONITORING AND IOT

Framework	Neural Units	Symbolic Units	Integration Insight
Capogrosso et al. [65], [66], [67]	Diffusion-based models for real-time anomaly detection in Industry 4.0.	Industrial ontologies for structured domain knowledge.	Enables context-aware anomaly detection with formal knowledge grounding.
Burghouts et al. [68]	Language-vision models generate probabilistic object proposals.	First-order logic defines spatial relations and object attributes.	Supports open-world visual reasoning and spatial interpretation in images.
Curry et al. [69]	DNNs for multimodal analysis (vision, audio, language).	Event processing rules for semantic and temporal reasoning.	Real-time multimodal event stream analysis with intelligent load-shedding.
Lu et al. (Bosch) [4]	Machine learning models for pattern extraction from manufacturing data.	Semantic ontologies model industrial assets and unify data formats.	Facilitates semantic integration and interoperable decision support.
Lee et al. (NSHD) [70]	CNNs for visual feature extraction in monitoring systems.	Hyperdimensional computing for symbolic, interpretable learning.	Achieves energy-efficient symbolic learning with reduced power use.

models, understand short-term semantics at the frame level, while symbolic units use state machines and temporal logic to reason over sequences. This architecture improves complex event recognition in video streams, outperforming GPT-4-based baselines by 9–15% in F1 score on challenging datasets such as Waymo and NuScenes [74].

F. Remote Sensing and Geospatial

In remote sensing and geospatial analysis, neuro-symbolic AI frameworks offer the potential to enhance semantic understanding by combining the perceptual strengths of neural networks with the contextual reasoning capabilities of symbolic systems.

Potnis et al. propose a framework where neural units consist of deep learning models used for analyzing high-resolution remote sensing imagery. These models perform core perception tasks such as land-use and land-cover classification, object detection, and segmentation. By learning from spatial and spectral patterns, the neural units generate rich embeddings that form the foundation for scene-level understanding [75]. Moreover, to enrich this understanding with contextual knowledge, symbolic units are introduced through Knowledge Graph Embeddings (KGE). These symbolic representations encode structured domain knowledge, such as relationships between land classes or geospatial entities, and allow the system to reason with background knowledge. The integration of KGE with neural models supports neuro-symbolic reasoning that improves both classification accuracy and semantic interpretability, especially in complex and ambiguous geographic scenes.

G. Audio and Speech Technologies

In the domain of audio and speech technologies, neuro-symbolic systems are increasingly being used to enhance human-computer interaction, adaptive communication, and speech enhancement under uncertain and noisy conditions. These hybrid systems combine the perceptual strength of neural models with symbolic reasoning frameworks for handling ambiguity and context-awareness.

Chen et al. present a framework that integrates neural networks with fuzzy logic to improve speech enhancement performance in dynamic and user-specific environments. The neural units form part of an adaptive fuzzy neural network that processes audio-visual signals. These units are responsible for learning from input data and adapting to varying environmental conditions, such as changes in signal-to-noise ratio, sound power, and the visual context accompanying speech [76]. The symbolic units are implemented using fuzzy logic, specifically a Sugeno-type fuzzy inference model. This symbolic component allows the system to incorporate rule-based reasoning to address real-world uncertainties and integrate clinically relevant variables such as cognitive load. The fuzzy rules are optimized using particle swarm optimization, enabling the system to make robust, interpretable decisions based on both learned patterns and symbolic reasoning.

H. General considerations of the importance of both neural and symbolic units in signal and image processing

1) Neural Units in Signal and Image Processing: Neural units in neuro-symbolic systems are typically responsible for perception and feature extraction tasks across various sensory modalities. They are implemented using deep learning architectures such as convolutional neural networks (CNNs), recurrent networks, vision-language models, or multimodal encoders, depending on the input type. In signal processing, neural units learn to extract hierarchical patterns from time-series data, such as audio signals or sensor streams, enabling tasks like speech enhancement, anomaly detection, or multimodal event understanding. In image processing and computer vision, they are used to perform object detection, semantic segmentation, scene classification, and visual grounding, often

TABLE V
COMPARISON OF NEURO-SYMBOLIC FRAMEWORKS IN MULTIMEDIA, VISION, AND ENTERTAINMENT

Framework	Neural Units	Symbolic Units	Integration Insight
Ritchie et al. [71]	Neural networks guide program synthesis and serve as primitives in visual DSLs.	Procedural symbolic programs define structure and logic using DSLs.	Combines neural guidance with symbolic generation for visual design.
Huang et al. (LASER) [72]	S3D video encoder and MLPs for extracting fine-grained video features.	Propositional logic and scene graphs represent spatio-temporal constraints.	Aligns video content with logic-based semantic goals for better video understanding.
Cingillioglu et al. (pix2rule) [73]	DNNs perform object detection and low-level visual recognition.	Rule learners apply symbolic logic to discover relations and patterns.	Enables interpretable rule-based reasoning from raw images.
Kim et al. (NeuroScene) [24]	ResNet and Mask R-CNN extract visual features and segment scene regions.	Semantic parser generates logic programs from natural language queries.	Supports reasoning over visual scenes through question-to-program translation.
Choi et al. (Video Search) [74]	Vision-language models process semantic content in individual video frames.	Temporal logic and state machines reason over video sequences.	Improves long-term event understanding with hybrid temporal reasoning.

TABLE VI
COMPARISON OF NEURO-SYMBOLIC FRAMEWORKS IN REMOTE SENSING AND GEOSPATIAL ANALYSIS

Framework	Neural Units	Symbolic Units	Integration Insight
Potnis et al. [75]	Deep learning models for scene classification, object detection, and segmentation.	Knowledge graph embeddings encode spatio-contextual and domain-specific knowledge.	Enhances scene understanding through integration of remote sensing data and geospatial knowledge.

TABLE VII
COMPARISON OF NEURO-SYMBOLIC FRAMEWORKS IN AUDIO AND SPEECH TECHNOLOGIES

Framework	Neural Units	Symbolic Units	Integration Insight
Chen et al. [76]	Adaptive fuzzy neural network processes audio-visual signals and learns context-specific features.	Sugeno fuzzy inference system handles uncertainty and integrates cognitive load reasoning.	Enhances speech processing through interpretable decision-making in noisy, real-world scenarios.

transforming raw pixel data into dense, structured feature representations. Neural units excel at learning from large datasets, adapting to complex input variability, and generalizing over high-dimensional feature spaces, which makes them ideal for perception-driven applications in communication, robotics, healthcare, and remote sensing.

2) Symbolic Units in Signal and Image Processing: Symbolic units in neuro-symbolic frameworks provide a structured reasoning layer that complements the learning capabilities of neural networks. These units encode domain knowledge, logical constraints, and interpretation rules, enabling systems to reason over the outputs of neural models in an interpretable and context-aware manner. In practice, symbolic components may include fuzzy logic systems, knowledge graphs, rule-based engines, domain-specific languages (DSLs), semantic ontologies, or spatio-temporal logic formalisms. They facilitate tasks such as program synthesis in graphics, temporal reasoning in video, semantic alignment in geospatial data, and clinical decision explanation in healthcare. By incorporating symbolic reasoning, systems can apply high-level logic to guide decisions, enforce safety constraints, resolve ambiguities, and support explainability—critical in domains that require trustworthy and transparent AI, such as industrial monitoring, medicine, and human-centered interfaces.

V. CHALLENGES IN NSAI

While neuro-symbolic AI holds great promise, several challenges must be addressed to fully realize its potential. Three main categories of challenges are discussed: computational challenges, integration challenges, and ethical (and societal) challenges.

A. Computational Challenges

Integrating neural and symbolic components in NSAI systems indeed presents significant computational challenges, primarily due to the inherent complexity of combining neural network training with symbolic reasoning. Neural networks, known for their substantial computational demands, are further burdened when logical constraints are embedded, as seen in frameworks like LNN, which can slow down convergence due to the dual requirement of data fitting and logical consistency [77]. Symbolic reasoning, particularly in tasks involving logic inference or combinatorial search, is computationally expensive, and when integrated with neural networks, it can lead to issues such as state-space explosion and longer training times [78], [77].

To mitigate these challenges, researchers are exploring various strategies. For instance, approximate reasoning techniques and knowledge distillation are being employed to transfer symbolic knowledge into neural models, thereby reducing the need for explicit reasoning during execution [3]. Additionally, more efficient neuro-symbolic architectures are being developed to address these computational inefficiencies. For example, the use of abductive reflection in neuro-symbolic systems has shown promise in efficiently rectifying reasoning inconsistencies by leveraging domain knowledge to flag and correct potential errors in neural outputs [79]. Furthermore, hardware-specific optimizations, such as those discussed in the context of vector-symbolic architectures, are being explored to enhance the performance and scalability of NSAI systems on existing hardware platforms [10].

These efforts are crucial as they aim to balance the computational load between neural and symbolic components, ensuring that NSAI systems can operate efficiently without compromising on their reasoning capabilities. The development of simulators like *LogiCity*, which provide customizable environments for testing complex reasoning tasks, also represents a significant step forward in advancing NSAI by allowing for the exploration of various abstraction levels and reasoning complexities [80].

Scalability in NSAI systems, particularly when applied to large-scale data such as high-resolution video or expansive sensor networks, remains a significant challenge due to the inherent complexity and computational demands of symbolic reasoning algorithms. Recent advancements have focused on optimizing solvers for differentiable logic constraints and leveraging parallel and distributed computing to manage the dual workload of learning and reasoning. For instance, the VERUS-LM framework addresses scalability by separating domain knowledge from queries and supporting a wide range of logical reasoning tasks, thereby enhancing adaptability and reducing computational costs [81]. Additionally, the integration of neuro-symbolic approaches in hardware architectures has been explored to improve efficiency and scalability. Studies have shown that neuro-symbolic models suffer from inefficiencies on conventional hardware due to memory-bound operations and complex flow control, prompting the development of cross-layer optimization solutions and hardware acceleration strategies [10].

In the realm of video question answering, the NS-VideoQA framework exemplifies the application of neuro-symbolic methods to improve compositional spatio-temporal reasoning, demonstrating enhanced performance in real-world tasks [82]. Furthermore, the *LogiCity* simulator introduces customizable first-order logic for urban environments, highlighting the potential of neuro-symbolic AI in handling complex, multi-agent interactions and long-horizon reasoning tasks [80]. These efforts collectively underscore the ongoing research aimed at ensuring NSAI solutions remain tractable and efficient for real-time and big-data applications, addressing both algorithmic and architectural challenges to enhance scalability and performance.

B. Integration Challenges

The integration of neural and symbolic representations in NSAI presents a significant challenge due to the inherent differences between continuous vector spaces used by neural networks and the discrete structures of symbolic AI. This gap can hinder effective communication between components, such as when a neural vision model detects objects but cannot translate these detections into symbols for a reasoning engine. Zhang and Sheng emphasize the need for intermediate representation spaces or interfaces to facilitate cooperation between neural and symbolic parts, which requires deep domain insight and iterative refinement [78]. Various approaches have been proposed to address this challenge. For instance, the NSA framework combines transformers with combinatorial search to narrow the search space and improve solution finding in the Abstraction and Reasoning Corpus (ARC) tasks, demonstrating a 27% improvement over state-of-the-art methods [78]. Meanwhile, Gustav Šír highlights the computational complexity of integrating neural and symbolic systems, noting that many methods simplify symbolic capabilities to fit within static tensor representations, which may not fully capture the symbolic paradigm's complexity [77].

In neuromorphic hardware, distributed representations have been used to embed symbolic computation into recurrent spiking neural networks, enabling robust multi-timescale computation without extensive parameter tuning [83]. NeSyCoCo leverages large language models to generate symbolic representations and map them to differentiable neural computations, achieving state-of-the-art results in compositional generalization tasks [26]. Additionally, *stl2vec* provides a method for embedding logic formulae into continuous spaces, facilitating integration into neuro-symbolic frameworks [84]. In educational applications, NSAI frameworks have been developed to incorporate symbolic educational knowledge into neural networks, enhancing interpretability and reducing biases [85], [9]. These diverse approaches illustrate the ongoing efforts to bridge the representation gap in NSAI, each contributing unique solutions to the integration challenge.

Maintaining consistency between neural and symbolic components in neuro-symbolic systems is a complex challenge that requires effective conflict-resolution strategies to prevent contradictory or unstable outcomes. One approach to address this issue is the use of soft constraints, where symbolic knowledge is imposed as penalties during neural network training, thereby reducing the likelihood of inconsistent outputs. This method is exemplified in the work of Calanzone et al., who introduce a loss based on neuro-symbolic reasoning to ensure logical consistency in language models, allowing them to adhere to external facts and rules while improving self-consistency even with limited data [86].

Another strategy involves iterative refinement loops, where symbolic reasoning can identify inconsistencies and prompt the neural component to relearn or adjust. This is seen in the work of Gu Baugh et al., who propose a neuro-symbolic approach that allows for manual intervention and adaptation of learned policies, thus facilitating the integration of symbolic rules into neural models [87]. Additionally, Xu et al. present *NeuRules*, a framework that unifies discretization, rule learning, and rule order into a single differentiable model, which helps in learning interpretable rule lists without pre-processing constraints, thereby addressing the instability in optimization [88].

Furthermore, the integration of symbolic reasoning with neural networks in autonomous systems, as discussed by Ogunsina et al., enhances decision-making by improving real-time contextual understanding and adaptability, which is crucial for maintaining consistency in dynamic environments [23]. These approaches highlight the importance of designing robust frameworks that can effectively manage the interplay between neural and symbolic components, ensuring that the system remains consistent and interpretable across various applications.

Interoperability and standards are also concerns. There is not yet a universally adopted framework or language for neurosymbolic integration. Researchers use a variety of tools (from probabilistic logic programming languages to neural network libraries), and combining these into a single coherent system can require substantial custom engineering. This slows down progress and makes it harder to reproduce results across projects. Efforts are underway to develop standard interfaces and platforms for NSAI, which would alleviate this challenge in the future.

C. Ethical and Societal Challenges

The integration of NSAI into autonomous systems, such as vehicles, introduces new dimensions to AI ethics and safety by combining symbolic reasoning with neural networks to enhance transparency and alignment with human values. This approach allows for the encoding of ethical principles and regulatory guidelines as symbolic rules, which can guide the decision-making processes of AI systems, such as autonomous vehicles, thereby improving accountability and explainability [89], [90]. The application of NSAI in autonomous driving systems is particularly significant, as it can incorporate explicit ethical rules, akin to variations of Asimov's laws or traffic regulations, to guide neural network behavior and prevent certain failure modes [91], [92]. This is crucial in scenarios where autonomous vehicles must make split-second decisions, such as unexpected pedestrian appearances or encounters with large animals, where ethical decision-making frameworks rooted in deontological principles can be applied to navigate these morally complex situations [90]. However, challenges remain in developing robust frameworks for implementing responsible AI principles within NSAI systems, as the complexities of merging neural and symbolic reasoning methods pose significant hurdles [89]. Moreover, the ethical implications of AI in autonomous systems extend beyond technical considerations, encompassing broader societal issues such as moral accountability, transparency, and the prioritization of human values [93], [94]. Addressing these challenges requires a multidisciplinary approach, integrating insights from ethics, law, and systems engineering to create comprehensive safety assurance models and enhance risk management strategies [95].

The complexity of NSAI systems, which integrate neural and symbolic components, poses significant challenges in ensuring reliability and trust, particularly in safety-critical applications such as medical diagnosis and autonomous driving. The unpredictability arising from potential disagreements between neural and symbolic components necessitates rigorous validation and verification processes. Techniques from formal methods are being explored to ensure that NSAI systems do not perform unsafe actions, thereby enhancing their reliability and trustworthiness. In the context of medical applications, AI's integration with blockchain technology in MedIoT systems aims to improve diagnostics and patient care while ensuring data security and privacy, which are crucial for building trust in these systems [96]. However, the safety of AI in medicine is a concern due to issues like algorithmic biases and data privacy, which must be addressed to ensure responsible AI deployment [97], [98]. In cybersecurity, the neuro-symbolic approach has shown promise in enhancing the detection and prevention of cyber threats in critical infrastructures, such as railway systems, by improving detection accuracy and response speed [99]. To address the reliability challenges in AI systems, frameworks that integrate reliability and resilience engineering principles are being developed, which apply traditional metrics like failure rate and Mean Time Between Failures (MTBF) to AI systems [97]. In aviation, the need for new reliability verification methods is emphasized due to the limitations of traditional approaches in handling the complexities of AI systems [100]. Furthermore, the development of explainable self-enforcing networks is proposed to assess compliance with safety standards in functional safety-critical systems [101]. The integration of responsible AI principles with NSAI systems is crucial for developing fair, explainable, and trustworthy AI technologies, although challenges remain in merging neural and symbolic reasoning methods [89]. In healthcare, enhancing guardrails for AI systems is necessary to manage risks such as hallucinations and misinformation, which can compromise patient safety [102].

Bias and fairness is another consideration. While symbolic knowledge could be used to correct biases in data (for instance, by providing fair reasoning rules or constraints), it could also introduce biases if the knowledge base or rules themselves are biased. An NSAI system might inherit biases from both its training data and its human-provided knowledge. Transparency in how the knowledge is sourced and used becomes important to mitigate this. Additionally, the ethical implications of decisions taken by NSAI should be continuously evaluated; having an explainable reasoning chain helps stakeholders to audit the system's behavior.

Finally, there is an educational and societal challenge: building interdisciplinary expertise. NSAI sits at the intersection of machine learning, knowledge representation, and specific application domains (like healthcare, robotics, etc.). Developing and deploying NSAI solutions requires collaboration between data scientists, domain experts, and knowledge engineers. Fostering this collaboration and training practitioners who understand both neural and symbolic techniques is vital for the field's progress.

VI. Future Trends in Neuro-Symbolic AI

NSAI is poised to significantly impact advanced signal and image processing in the coming years. This integration of neural networks and symbolic reasoning offers a promising pathway to enhance AI's capabilities in various domains. The future trends and research directions in NSAI include deeper integration with large-scale neural models, automated knowledge extraction and learning, application in edge and real-time environments, enhanced explainability and user interaction, and cross-domain generalization. These trends are expected to drive the evolution of NSAI, making it more robust, efficient, and applicable across diverse fields.

- **Deeper Integration with Large-Scale Neural Models**
  NSAI aims to combine the strengths of neural networks and symbolic reasoning, addressing the limitations of each approach when used independently [3]. Large-scale neural models, such as those used in deep learning, can benefit from symbolic reasoning to enhance interpretability and robustness [10]. The integration of symbolic techniques with neural networks can lead to more efficient and scalable AI systems, as demonstrated by the Neuro-Photonix framework, which reduces power consumption significantly while maintaining accuracy [53].
- **Automated Knowledge Extraction and Learning**
  Knowledge graphs play a crucial role in NSAI by providing structured representations that enhance reasoning and interpretability [103]. Automated knowledge extraction can be achieved by leveraging the strengths of both neural and symbolic systems, allowing for more accurate and complete symbolic systems [103]. The use of multi-scale convolutional neural networks (CNNs) for hierarchical signal feature extraction exemplifies how NSAI can optimize communication protocols autonomously [15].
- **NSAI in Edge and Real-Time Environments**
  NSAI's application in edge and real-time environments is facilitated by advancements in hardware architectures, such as the Neuro-Photonix accelerator, which supports near-sensor computing [53]. The ability to process data efficiently at the edge is crucial for applications in autonomous systems and IoT, where real-time decision-making is essential [15], [53].
- **Enhanced Explainability and User Interaction**
  Explainability remains a significant challenge in NSAI, with efforts focused on making model decisions and predictions more understandable [14]. Enhancing explainability is crucial for building trust in AI systems, particularly in fields where transparency is essential [12], [14]. Interdisciplinary research is needed to address gaps in explainability and trustworthiness, which are less represented in current NSAI research [12].
- **Cross-Domain Generalization**
  NSAI's potential for cross-domain generalization is highlighted by its ability to learn and apply information in unexpected settings, a key aspect of compositional generalization [104]. The flexible assembly of existing building components in NSAI architectures can facilitate the application of AI across diverse domains, enhancing its adaptability and utility [104].

VII. Conclusions

With its hybrid architecture that balances the logical reasoning and structure of symbolic AI with the data-driven learning capabilities of neural networks, NSAI is at the front of a paradigm change in artificial intelligence. AI systems may now function more transparently, reliably, and interpretably across a variety of signal and image processing applications because to this convergence. NSAI has shown great promise in connecting low-level perception with high-level reasoning in a variety of fields, from communication systems and autonomous robotics to healthcare and industrial monitoring. This has allowed NSAI to surpass conventional purely neural or symbolic approaches in terms of generalisation, adaptability, and explainability.

The paper has provided a structured exploration of various NSAI architectures, illustrating how each design facilitates different levels of integration and interaction between neural and symbolic modules. Applications reviewed across multiple domains confirm the growing maturity and versatility of NSAI frameworks. Examples such as DeepSym in robotics, MediSage in healthcare, and Neuro-Photonix in edge computing highlight how NSAI can tackle complex tasks by combining learning with explicit knowledge representation. Moreover, the surveyed studies underscore that NSAI systems not only improve performance but also enable critical functions such as rule enforcement, ethical decision-making, and real-time responsiveness.

However, there are still major obstacles to overcome. To fully realise the potential of NSAI, it is necessary to address computational inefficiencies, integration challenges, and ethical concerns about bias, transparency, and accountability. These systems' dual nature adds complexity, necessitating improvements in knowledge representation, hardware acceleration, cross-domain modelling, and interface standardisation. Furthermore, the responsible use of these technologies will heavily depend on societal preparation, which can be achieved through inclusive design, interdisciplinary education, and ethical alignment.

Future studies must focus on creating NSAI systems that are reliable, standardized, and scalable. Promising opportunities to increase the influence of NSAI across industries are presented by emerging trends such as automated knowledge synthesis, edge intelligence, and compositional generalization. The combination of neural learning with symbolic thinking provides a strong basis for next-generation intelligent systems, which will not only function well but also more closely match human expectations for safety, fairness, and explainability as AI becomes more widespread.

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Conflits of Interest

The author declares no conflict of interest.

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