A Study on Neuro-Symbolic Artificial Intelligence: Healthcare Perspectives

Delower Hossain^{1,3}, Jake Y Chen * 1, 2, 3

Abstract— Over the last few decades, Artificial Intelligence (AI) scientists have been conducting investigations to attain humanlevel performance by a machine in accomplishing a cognitive task. Within machine learning, the ultimate aspiration is to attain Artificial General Intelligence (AGI) through a machine. This pursuit has led to the exploration of two distinct AI paradigms. Symbolic AI, also known as classical or GOFAI (Good Old-Fashioned AI) and Connectionist (Sub-symbolic) AI, represented by Neural Systems, are two mutually exclusive paradigms. Symbolic AI excels in reasoning, explainability, and knowledge representation but faces challenges in processing complex real-world data with noise. Conversely, deep learning (Black-Box systems) research breakthroughs in neural networks are notable, yet they lack reasoning and interpretability. Neuro-symbolic AI (NeSy), an emerging area of AI research, attempts to bridge this gap by integrating logical reasoning into neural networks, enabling them to learn and reason with symbolic representations. While a long path, this strategy has made significant progress towards achieving common sense reasoning by systems. This article conducts an extensive review of over 977 studies from prominent scientific databases (DBLP, ACL, IEEExplore, Scopus, PubMed, ICML, ICLR), thoroughly examining the multifaceted capabilities of Neuro-Symbolic AI, with a particular focus on its healthcare applications, particularly in drug discovery, and Protein engineering research. The survey addresses vital themes, including reasoning, explainability, integration strategies, 41 healthcare-related use cases, benchmarking, datasets, current approach limitations from both healthcare and broader perspectives, and proposed novel approaches for future experiments. Moreover, it identifies critical challenges in applying Neuro-Symbolic AI to medicine and represents a comprehensive exploration of its transformative potential in the biomedical field.

Keywords: Neuro-Symbolic Artificial Intelligence, Cogitative Intelligence, Knowledge Representation and Reasoning, Machine Learning, Deep Learning, Hybrid System.

I. INTRODUCTION

A is an interdisciplinary field integrating cognitive science, philosophy, psychology, computer science, neuroscience, and other domains. At its core, modern AI is anticipated by deep learning, the main component of which is artificial neural networks (inspired by neurons workings of the human brain) [1]. Geoffrey Hinton, along with David E. Rumelhart et al., published an article in 1986 titled "Learning representations by back-propagating errors," which is widely

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recognized for reformulating and popularizing the backpropagation algorithm for training multilayer neural networks. He was awarded the 2024 Nobel Prize in Physics [2]. Autonomous vehicles, galaxies, and stars classification became a reality by leveraging this technology. However, despite AI's breakthroughs, interpretability, explainability, and reasoning remain opacity—critical aspects for secure applications such as in healthcare and autonomous systems. Neuro-symbolic AI (NeSy) addresses this gap by blending neural networks with explainable symbolic logic, facilitating reasoning, interpretability, and scalability in AI. To recognize how NeSy bridges the divide, it is essential to explore the foundations of AI, which are rooted in two paradigms: Symbolism and connectionism.

Symbolic AI, often referred to as Good Old-Fashioned Artificial Intelligence (GOFAI), represents a classical approach focusing on knowledge representation. This paradigm dominated the classical Artificial Intelligence era from the 1950s to the 1980s [3]. A defining characteristic of symbolic methods is their capacity for explanation and reasoning, facilitating decision-making processes. Symbolic techniques encompass explicit symbolic methods such as programming languages, first-order logic, propositional logic, and domain-specific symbolic expressions. Other procedures include rules, knowledge graphs, ontologies, decision trees, and symbolic

expressions. However, a notable limitation of this approach is its inability to manage large-scale and noisy data effectively.

Sub-symbolic AI is an approach to Artificial Intelligence distinct from Symbolic AI, often described as a "black box." This black-box system draws on large-scale data, typically for statistical learning. Its development accelerated with the pioneering work of "godfathers" of deep learning [4]researchers such as Geoffrey Hinton, Yann LeCun, and Yoshua Bengio-who contributed to fundamental advancements in connectionist approaches. An essential building block of Sub-Symbolic AI is the perceptron, developed by Frank Rosenblatt in the 1950s, while McCulloch and Pitts developed the early neuron model in 1943 [3]. The perceptron is a type of artificial neuron. Multilayer Perceptrons (MLPs) [5] and Deeper Neural Networks have since evolved, greatly extending the capabilities of Sub-Symbolic AI to handle complex, nonlinear problems. While Sub-Symbolic AI excels at pattern recognition and can hold vast amounts of unstructured and noisy data, it often lacks explainability and reasoning. This lack of transparency has led to the label of a "black box" approach, as its complex internal computations are typically opaque to users, making it challenging to interpret how decisions are made. Nevertheless, Sub-Symbolic AI remains integral to advancements in fields such as autonomous systems and healthcare due to its incapability and reasoning. As such, a new dimension of AI has captured the interest of researchers over the past decades.

Neuro-symbolic AI is a novel branch of Artificial Intelligence that aims to overcome the limitations of both symbolic and connectionist approaches by integrating their strengths. This integration seeks to develop AI systems that are not only explainable and interpretable but also capable of reasoning. In the 1990s, Geoffrey G. Towell presented new AI approaches recognized as Knowledge-Based Artificial Neural Networks (KBANN) (1994)[6] and NofM (1991)[7]. Recent research in Neuro-symbolic AI has yielded cognitive simulations and frameworks for learning, reasoning, and language, such as NS-VQA [8], achieving 99.8% accuracy on the CLEVR dataset. Numerous models and frameworks, such as; LTN [9], LNN [10], DFOL-VQA [11], FSKBANN [12], MultiPredGO [13], DeepMiR2GO [14], ExplainDR [15], PP-DKL [16], FSD [17], CORGI [18], KGCNN [19], NeurASP [20], have been developed during this period, showing promising performance in the biomedical and other sectors. This study examines the role of Neuro-symbolic AI (NeSy) in healthcare settings, focusing on its applications in biomedical use cases, model performance, implications for medical datasets, and emerging trends while evaluating state-of-the-art NeSy algorithms. Additionally, it offers simulation insights into drug discovery and presents a novel approach to advancing the protein-drug interaction use case task.

The article presents a comprehensive survey, evaluation, and analysis of the promising Neuro-Symbolic (NeSy) paradigm. The enhanced outline of the article is as follows: Section II outlines the study's process and methodology, followed by an overview of Neuro-symbolic AI, its categorizations and principles, and reviews contemporary models and approaches, including their results in Section III. Section IV focuses on NeSy applications in healthcare, while Section V addresses open challenges and limitations. Section VI proposes a new method and discusses future outlooks, with the article concluding in Section VII. To our knowledge, no prior survey or systematic review has explicitly focused on Neuro-Symbolic AI in healthcare perspectives, although several reviews in other domains have observed [21]- [43].

Key contributions:

- An overview of real-life application exploration of Neuro-Symbolic AI in Healthcare.
- Proposed novel approaches using large chemical-protein language models and Logic Tensor Networks for compound-protein interaction tasks.
- Comprehensive analysis of recent neuro-symbolic domains of applications uncovered promising models for benchmarking, dataset, model evaluation, healthcare, and the no-healthcare perspective.
- Revealed practical simulation results of NeSy approaches in drug discovery (Cardiotoxicity, Diabetes, and TNBC compound classification).
- Summarized Existing model strengths (Reasoning, Interpretability) and limitations.
- Identified open challenges in applying Neuro-symbolic AI to Biomedical field.

II. METHODOLOGY

This section serves research questions, article selection criteria, and data extraction methods applied to studies across healthcare and non-healthcare domains.

Research Questions

RQ1: What are the recent advancements in Neuro-symbolic AI techniques and methodologies in healthcare and non-healthcare settings?

RQ2: What are the emerging trends and potential Applications of Neuro-Symbolic AI in the biomedical domain?

RQ3: What are the benefits of integrating the machine learning paradigm with the Knowledge base system in the healthcare field?

RQ4: What are the Challenges & limitations of integrating ML and Symbolic reasoning?

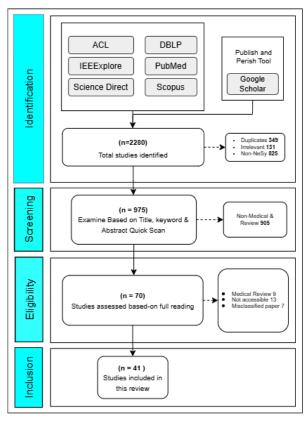


Fig. 1 NeSy Literature Collection Flow Chart

To identify relevant studies, an initial search retrieved 2,280 scientific articles from digital databases such as ACL, IEEE Xplore, ScienceDirect, DBLP, PubMed, Scopus, and NeurIPS, ICML Fig.1. For databases like ACL, PubMed, and Google Scholar, we collected by manual search (CSV). DBLP was Jason format and Science Direct BibTex format. We used Paperpile, an online tool mainly used for Science Direct BibTex to CSV conversion. Afterward, we used Python & pandas to handle Jason format and data preprocessing.

In the identification stage, we eliminated duplicates, irrelevant articles, inaccessible sources, and non-medical studies, narrowing down to 975 manuscripts on neuro-symbolic themes. Further screening excluded 905 non-medical articles based on title, keywords, and abstracts. Applying eligibility criteria and research questions, we finalized 41 biomedical-relevant studies. We prioritized the biomedical domain and included promising models and relevant articles potentially applicable to healthcare. From the eligible articles, we extracted details such as (a) Title, (b) Model Performance metrics, f(c) Results, (d) Source/Venue, (e) Domain, (f) Publication Year, (g) Model Reference, (h) Dataset, (i) NeSy category, (j) Integration type, and additional symbolic and sub-symbolic terms.

Resources & Supplementary materials:

All statistics, facts, figures, tools, and supporting materials leveraged in this study can be acquired upon requesting to upon request to mhossai5@uab.edu.

III. NEURO SYMBOLIC ARTIFICIAL INTELLIGENCE

The roots of Neuro-symbolic AI, merging symbolic reasoning and neural processing, can be traced back to McCulloch and Pitts' 1943 innovation [44]. McCulloch and Pitts' work was an avant-garde in its use of propositional logic to model with neural computation. Since the late 1980s, there has been ongoing debate [45] about the need for a cognitive sub-symbolic level in AI. In artificial Intelligence (AI), perception and cognition are represented by two foundational paradigms: connectionism (neural systems) and symbolism, or knowledge-based systems. Each approach has been a dominant influence in the field for decades after decades. Connectionism focuses on pattern recognition and learning but is unable to interpretability and reasoning, and symbolism emphasizes logic and rule-based reasoning but has flaws in learning from big and noisy data. Neuro-symbolic AI combines symbolic reasoning (Knowledge-based, logical systems) with deep learning (datadriven, statistical methods) to create AI systems capable of accomplishing cognitive tasks. Literature evident [27] that the primary goals of Neuro-Symbolic AI (NeSy) include but are not limited to generalization, interpretability, explainability, reasoning, error handling/root cause identification, out-ofdistribution handling, scalability with minimal data, transparency, trustworthiness, reduced computational complexity, and energy efficiency. However, an underlying comparison will make it easy to understand both domains.

A. Fundamental Comparison

The fundamental distinctions between symbolic, subsymbolic, and neuro-symbolic AI reflect their attributes and approaches toward intelligence jobs. Literature suggests [3] Symbolic AI, or symbolism, relies on explicit signs, logical reasoning, serial processing, and static structures respectively. It requires human intervention and precise inputs and focuses on concept composition and model abstraction. By contrast, sub-symbolic AI, represented by connectionism, employs statistical methods and associative, parallel processing in dynamic systems. It's flexible, adapts to noisy or incomplete data, generalizes from large datasets, and supports concept creation through learning. Neuro-symbolic AI aims to merge these paradigms, leveraging the strengths of symbolism.

Reasoning and sub-symbolic learning to achieve attributes like interpretability, scalability, error handling, and generalization, advancing model transparency and robustness with less reliance on extensive data. However, Table 1 illustrates a core comparison among Symbolic, Sub-symbolic, and Neuro-symbolic AI.

Table 1: A Com	parison Presentation	of Symbolic	, Sub-symbolic,	and Neuro-S	ymbolic [46]

	1	, , ,	J 2 3
Aspects	Symbolic	Sub-symbolic	Neuro-symbolic
Methods	Mostly logical and algebraic	Mostly analytical & numeric	A combination of logic and numeric
Strengths	Productive, recursion principle,	Robustness, Learning	High efficiency, data accuracy,
2	compositionality	Ability, Adaptivity	learning & reasoning
Weaknesses	Consistency constraints, lower	Opaqueness, Higher	Complex to set up rules with
· · · carriesses	cognitive abilities	Cognitive Ability	connectionist
Applications	Reasoning, problem-solving	Learning, control, vision	Control the quality, detection,
Applications	Reasoning, problem-solving	Learning, control, vision	classification
Cog. Science	Not biologically inspired	Biologically inspired	Integration of genetic-inspired ANN &
Cog. Science	Not biologically hispited	Biologicany inspired	rules

B. Categories and Integration Strategies

In the AAAI 2020 Robert S. Engelmore Memorial Award Lecture, Henry Kautz outlined five categories of Neurosymbolic AI systems to discuss the future of AI [21]. Type 1 (symbolic-neuro-symbolic), Type 2 (symbolic [neuro]), Type 3 (neuro; symbolic), and Types 4 and 5 (neuro: symbolic → neuro and neuro_symbolic) (Table 2). Similarly, W. Wang et al. proposed six neuro-symbolic types [47], while K. Hamilton [27] consolidated these into three: ensemble, sequential, and integrated, merging Kautz's categories.

Table 2: NeSy Kautz's category

Kautz's Category	Description	Reference
NEURAL NETWORK		word2vec [177]
Symbols Symbols	Symbolic Neuro Symbolic	Glove [178]
4		GPT-3 [179]
		AlphaGo [180]
		NeSS [181]
SYMBOLIC MODEL		PLANS [182]
NEURAL NETWORK	2. Symbolic [Neuro]	VisProg [154]
		HuggingGPT [183]
		ViperGPT [184]
		NVSA [185]
		NeuPSL [186]
SYMBOLIC MODEL NEURAL NETWORK		NSCL [160]
	3. Neuro Symbolic	NeurASP [20]
		ABL [187]
		NSVQA [8]
SYMBOLIC SYMBOLIC SYMBOLIC SYMBOLIC SYMBOLIC SYMBOLIC		LNN [10]
compile NEE RAL NETWORK	4. Neuro: Symbolic → Neuro	Symbolic Mathematics [188]
NEI EAL NETWORK Training data		Differentiable ILP [189]
		LTN [9]
		Deep ontology networks [58]
NEURAL NETWORK SYMBOLIC		Logistic Circuits [190]
Output KNOWLEDGE	5. Neurosymbolic	LRI [191]
(%.£0.%)	STREOLIC	HDNNLR [192]
		LFS [193]
		Semantic Loss [61]
		DANN [194]
NEURAL NETWORK		GNN+attention [20]
0 0 0 0 0 0 0 0 0		NLM [54]
08~808~808~808~8080>o	6. Neuro[Symbolic]	SATNet [195]
Neuro Logic		GVR [196]
Unit Unit		LogicSeg [197]
Note: Visual diagram adopted from [39]		

Furthermore, the study was published in 2005 by M. Hilario [48]. Neuro-symbolic AI approaches were classified across

eight dimensions, grouped into three main aspects: Integrated vs. Hybrid, Neuronal vs. Connectionist, and Local vs. Distributed types. Notably, no single approach was deemed universally superior; rather, the choice of approach depends on specific domain requirements, tasks, and contextual considerations.

Likewise, from a general point of view, two main engines are typically employed in neuro-symbolic integration: symbolic and neural components. Studies underscore knowledge graphs, decision trees, first-order logic [9], fuzzy logic [9], programming languages like Prolog [49], and symbolic expressions [7],[8] as central to the symbolic side. In addition, transformers and large language models (LLMs) are being integrated into the neural component to enhance the system's learning and reasoning capabilities.

Furthermore, the applications of neuro-symbolic AI span diverse domains. IBM Research's "Survey on Applications of Neuro-Symbolic Artificial Intelligence" highlights a range of fields. In this study, we broaden the focus by including models applied in healthcare (the primary focus), as well as cybersecurity, recommendation systems, robotics/automation, smart cities, information retrieval, NLP, VQA, computer vision, digital twins, generative AI, military applications, and marine vessel management. An outline table of application domains, models, and references is available in Appendix A. In addition, Table 3. It serves as a benchmarking summary and performance result for several leading approaches.

C. Neuro-Symbolic Reasoning & Explainability

From a symbolic perspective, reasoning is conducted explicitly through rules or logic, representing the cognitive process of concluding, making decisions, or solving problems based on available information, knowledge, or evidence. Key types of reasoning include deductive, inductive, abductive, analogical, probabilistic, and causal reasoning. In the context of

neuro-symbolic AI, Logic Tensor Networks (LTN) [9] integrate logic-based rules expressed in first-order logic (FOL). For example, in healthcare, a rule might state, "If a drug has a Toxicity concentration score below 5, it is safe." Given a drug with a toxicity score of 3, the system concludes that the drug is safe based on this biomedical rule. Knowledge is represented through FOL and integrated via a loss function in LTN, which enhances the system's significance in healthcare by incorporating medical knowledge, reducing the likelihood of misdiagnosis, and enabling healthcare professionals to comprehend the underlying logic. Table 4 below illustrates how different approaches formalize knowledge/rules. Additionally,

Explainability aims to make AI decisions and processes understandable to humans, clarifying the reasoning behind a model's predictions or decisions. Several ways can be achieved in explainabilities. For instance, Post-hoc Explanation methods, Feature-level explainability, Rule/Knowledge-Based Explainability, and Process/System Explainability are notable. Explainability in neuro-symbolic AI often relies on knowledge-based components (Symbolic Components). NS-VQA, explainDR, and Greybox-XAI are examples of the NeSy explainable model. Explainability is pivotal in healthcare for building trust and accountability of AI systems.

Table 3: Benchmarking Summary of Leading Approaches

Model	Dataset	Metric	Result	Source/Institution	Business Domain	
NS-VQA [8]		Accuracy	99.80	IBM		
NS-CL [50]	CLEVR	Accuracy	96.90	DeepMind & MIT	VQA	
XNMs [57]		Accuracy	100.00	IEEE		
Prob-NMN [59]		Accuracy	95.63	MLR Press		
DL2 [60]		Accuracy	97.60	MLR Press		
Semantic Loss [61]	MNIST	Accuracy	99.36	MLR Press	Classification	
LTN [9]		Accuracy	98.04	Sony AI		
Faster LTN [62]	PASCAL VOC	mAP	73.80	Springer	Object Detection	
Neural LP [63]	UMLS, Kinship	MRR	94.00	Neurips	****	
RRN [58]	Family Trees	Accuracy	99.90	IJCAI	 Link Prediction 	
Grail [64]	NELL-995	AUC-PR	98.11	ICML	Relation Prediction	

Table 4: NeSy Symbolic Expression

RULES	Expression	Model
First-Order Logic	$\forall \mathbf{x}_{\mathbf{A}}, p(\mathbf{x}_{\mathbf{A}}, \mathbf{l}_{\mathbf{A}}), \forall \mathbf{x}_{\mathbf{B}}, p(\mathbf{x}_{\mathbf{B}}, \mathbf{l}_{\mathbf{B}})$	LTN
Fuzzy Logic	$F = \forall x (isCarnivor(s)) \rightarrow (is Mammal(x))$ $\{isCarnivor(s): [0,1], is Mammal(x): [1,0]\} \rightarrow F = [1,0]$	LTN
Logic Rules	Domain: $animal(dog)$. $carnivore(dog)$. $mammal(dog)$ Logical formula: $mammal(x) \land carnivore(x)$ ABL: $hypos(x) := animal(x), mammal(x), carnivore(x)$	ABL
Problog	$ flip(coin1).flip(coin2). \\ nn(mside,C,[heads,tails]):: \\ side(C,heads); side(C,tails).t(0.5):: red; t(0.5)::blue. \\ heads:-flip(X),side(X,heads). \\ win:-heads. \\ win:-+heads,red. \\ query(win). $	DeepProblog
Symbolic Expression	equal_shape: (entry, entry → Boolean equal_size (entry, entry) → Boolean	NS-VQA

Table 5: Selected Models Goals and Principles Summary							
	Model	Authors	Year	Knowledge Representation	Interpretability	Reasoning	Explainability
1.	KBANN	GG Towell et al.,	1994	Propositional Logic		✓	
2.	CLIP	A d'Avila Garcez et al.,	1999	Propositional Logic		✓	
3.	NS-VQA	K Y et al.,	2018	Symbolic Expression			~
4.	DeepProbLog	R Manhaeve et al.,	2018	First-Order Logic		✓	
5.	NS-CL	J Mao et al.,	2019	Symbolic Expression		✓	
5.	XNMs	J Sh et al.,	2019	Knowledge Graph			~
7.	XAI	M Drance et al.,	2021	Symbolic Expression			~
3.	ExplainDR	S I Jang et al.,	2021	Symbolic Expression	✓		,
).	NS-QAPT	C Ashcraft et al.,	2023	Symbolic Expression			,
0.	Greybox XAI	A Bennetot et al.,	2022	Symbolic Expression			•
1.	X-NeSyL	N D Rodríguez et al.,	2022	Symbolic Expression			,
2.	NS-ICF	W Zhang et al.,	2022	Symbolic Expression			,
3.	SenticNet	E Cambria et al.,	2022	Symbolic Expression	✓		,
4.	HRI	C Glanois et al.,	2022	First-Order Logic	✓		
5.	LTN	D Onchis et al.,	2022	First-Order Logic		✓	
6.	EIC	S Haji et al.,	2023	Symbolic Expression	✓	✓	
7.	KD-LTN	H D Gupta et al.,	2023	First-Order Logic	✓	✓	
8.	GNN	Raj K et al.,	2023	Symbolic Expression	✓		
9.	NEUROSIM	Singh H et al.,	2023	Symbolic Expression	✓	✓	
0.	NSIL	Cunnington D et al.,	2023	Symbolic Expression	✓	✓	
1.	TACRED	R Vacareanu et al.,	2023	Symbolic Expression	✓	✓	,
22.	NSHD	H Lee et al.,	2023	Symbolic Expression			,
23.	TON-ViT	Y Zhuo et al.,	2023	Symbolic Expression			,
4.	DeepPSL	S Dasaratha et al.,	2023	First-Order Logic		✓	,
5.	S-REINFORCE	Dutta R et al.,	2024	Symbolic Expression	✓		
6.	DVP	Cheng Han et al.,	2024	Symbolic Expression			,
7.	X-VQA	A Mishra et al.,	2024	Symbolic Expression			,
8.	MARL	C Subramanian et al.,	2024	First-Order Logic	√		
29.	NS-RL	L Luo et al.,	2024	First-Order Logic	✓		,

IV. NEURO SYMBOLIC AI IN HEALTHCARE

Artificial Intelligence in healthcare has transformed clinical domains by enhancing disease surveillance, drug development, diagnostics, prognostics, treatments, cancer research, genomic study, and protein research. A recent breakthrough is the invention of AlphaFold. This revolutionary AI system predicts

the 3D proteins' highly accurate structure based on amino acid sequences developed by John Jumper (DeepMind). He was awarded the 2024 Nobel Prize in Chemistry for their work [65]. Despite these promising advances, several challenges remain, including the need for transparent, explainable, robust AI models. The World Health Organization's 2021 guidance on the

ethics and governance of AI in healthcare outlines six core principles to ensure AI benefits people globally [66]. The principles of transparency, explainability, and intelligibility are focal and highlighted, emphasizing the need for AI systems. As such, Neuro-symbolic AI promises to revolutionize healthcare by combining the strengths of neural networks (robust pattern recognition) and symbolism (reasoning and explainability). The explainable nature of symbolic methods enhances decision-making by providing clinicians with understandable justifications for AI-driven diagnoses and treatment plans, fostering trust and collaboration. This improves patient care through more reliable, transparent, and interpretable AI systems.

In this survey, various approaches and domains of application discovered that have emerged in Neuro-symbolic AI in the past ten years, advocating great potential regarding knowledge representation, reasoning, explainability, and interpretability. This section aims to present 41 eligible articles on Neuro-symbolic healthcare and their empirical results, with the core findings focusing on their application in the medical domain. Table 6 provides insights into significant models, including their performance metrics, neural and symbolic integration terms, year of publication, and dataset. Furthermore, the following list highlights diverse use cases that demonstrate NeSy's applicability across various medical and biological domains that our study revealed:

Phenotype-driven variant prioritization [67], ontologybased chemical classification[68], LUS-based COVID-19 severity assessment[69], high-order relationships for hyperlink prediction[70], molecular generation[71], mental disorder diagnosis[72], toxicity prediction[73], COVID-19 patient stratification[74], seizure detection[75], link prediction[76]-[78], wound healing stage prediction[79], early depression detection[80], detection and segmentation of cerebral aneurysms in two-dimensional digital subtraction angiography (DSA) images[81], ontological classification[82], E. Coli promoter gene sequences (DNA) classification [6][83], genetic sequence classification[84], classify protein secondary structure prediction[12], protein folding predictions[85][86], pulmonary embolism diagnosis [87], predicting cell states from gene expression profiles [88], probability prediction of age from gene expression records of skin tissue [89], classification of cell types and states [28], treatment of specific diseases [91], heart failure classification [94], question and a relevant piece of medical literature (a context) [93], protein function prediction [13], ontology-based classification[94], target gene prediction [14], predicting interactions between proteins [95], diabetic retinopathy classification [15], semantic classification [96], temporal series classification problem [97], neurodegenerative diseases[16], pattern recognition in cardiotocograms [98],

aphasia diagnosis [99], i2b2 2008 obesity challenge classification [19], breast tissues classification [100].

Additionally, integrating data and knowledge enables advancements in various biomedical, chemoinformatics, and applications that can accurately diagnose diseases, discover potential drug targets, den novo drug and artificial protein design, medical imaging, Cardiotoxicity, and Ophthalmology. Some of the practical domain applications of NeSy are as follows:

A. Drug Discovery and Cheminformatics

Usually, the drug development process—from target discovery to regulatory approval—typically spans 12 to 15 years and costs approximately \$2.8 billion [101]. Moreover, global drug sales are forecasted to reach \$1.9 trillion by 2027 [101]. In the Generative AI Era, an opportunity opens to reduce these timeframes and costs significantly. For instance, models like Llamol have demonstrated impressive accuracy, generating novel valid molecules with 97-99% [102]. However, they rely heavily on data-driven approaches. Combining symbolic reasoning with neural networks, Neuro-Symbolic AI models like Logic Tensor Networks (LTN) (Fig. 2) enhance predictive power; in our trials, LTN and DeepProbLog achieved around 97% accuracy in classifying drug efficacy and bioactivity for and cancer (TNBC) inhibitors bio-activity classification employed ChEMBL dataset [103], outperforming conventional DNNs and transformer models like RoBERTa. The adaptability of LTN extends to the following applications: drug sensitivity, synergy, toxicity, resistance, response, multi-target drug discovery, molecular optimization, and binding affinity prediction. In addition, authors M. Drance, and T.T. Ashburn have discovered a new use of existing drugs, which is known as drug repurposing using the NeSy approach [76][104].

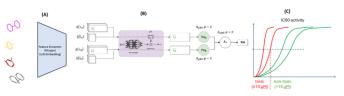


Fig.2: LTN architecture (B)

B. Protein Research

Proteins play an essential role in biology, from blocking infections to harnessing solar energy, vision, blood clotting, immune system response, hormone regulation, and cell and tissue repair. Understudying the correct structures and highly accurate folding is vital. Unfolded or misfolded proteins may cause degenerative diseases, including Huntington's diseases, Alzheimer's, Parkinson's, and cystic fibrosis. Recent AlphaFold's groundbreaking innovations have ushered in a new

era of computational protein engineering research, delivering highly accurate protein structure predictions. Prof. David Baker from the University of Washington received a Nobel Prize for pioneering de novo protein design [65], an accomplishment that allows scientists to create custom proteins from scratch. In the realm of Neuro-Symbolic AI, research can be expanded into protein folding prediction [85][86], protein structure prediction[12], and protein function analysis. By integrating AlphaFold's capabilities with symbolic reasoning, researchers can enhance the precision of protein-protein interaction predictions that can unlock new insights for targeted drug design and synthetic biology applications.

C. Visual Question Answering (VQA)

Transparency and interpretability are keys in healthcare that improve reliability and trustworthiness in the AI system. Integrating medical domain-specific knowledge with neural networks [105][106] is an emerging field that enables more accurate, context-aware predictions and enhances the interpretability of AI models, flooring the way for improved diagnostics, personalized treatments, and advanced therapeutic discoveries. NeSy approach has made significant contributions in this domain, identifying more than 51 robust, visual reasoning, interpretable, and explainable models [107]-[157]. To be exemplified, NS-VQA [8], developed by IBM, MIT, and DeepMind, combines symbolic reasoning with deep learning to answer questions about images. It interprets visual scenes by translating them into symbolic representations, allowing for logical reasoning over objects, and achieved 99.80% accuracy on CLEVR benchmarks, whereas the NS-CL model yields 96.90% accuracy [50]. In this field, some frequently used benchmarks datasets are VOA 1.0 dataset [161], CLEVR datasets [159], GQA dataset [162], CLEVR-CoGenT [159], and SHAPES dataset [163], selected models that can be translatable into Med-VQA such as NS-VQA, XNMs[57], NMN[56], N2NMN[164], NSM[165], VRP [176].

D. Ophthalmology & Cardiotoxicity

In ophthalmology, Neuro-symbolic AI combines symbolic reasoning with pattern recognition to enhance diagnostic and treatment explainability, enabling interpretable and accurate assessments of eye conditions such as diabetic retinopathy and glaucoma. This approach improves detection accuracy and adds transparency, aiding ophthalmologists in understanding AI-driven decisions. ExplainDR[15] uses a feature vector as a symbolic representation for explainable diabetic retinopathy (DR) classification Fig. 3. Additionally, the NeSyL[34] study proposes viable neuro-symbolic approaches for clinical settings with potential applications in diagnosing and predicting ocular diseases and in health informatics.

Furthermore, we conducted simulations assessing the cardiotoxic effects of drug molecules using Logic Tensor Networks (LTN) Fig. 3. We constructed a hERG-related dataset by combining ChEMBL[103], hERG Karim[167], BindingDB [168], PubChem[[169], hERG Blockers[110], and GTP datasets[171]. LTN outperformed models such as M-PNN [172], OCHEM Predictor-II [167], Random Forest [173], CardioTox[167], ADMETlab 2.0[174], and Gradient Boosting[175], achieving higher accuracy, with an ACC of 0.827 and a specificity (SPE) of 0.890 on the hERG-70 benchmark [202] (Fig., 2).

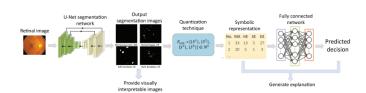


Fig. 3: ExplainDR Architecture

Table 6: An overview of recent NeSv models in healthcare with performance metrics	Table 6: An overview	of recent NeS	v models in healthcare	with performance metrics
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	Method	Model Inte	Dataset	Metrics Type	Result	Year	Venue/Source	Reference
1.	KBANN	PR+DL	Promoter Dataset	Error Rate	4/106	1990	ACM	[83]
2.	KBANN	PR+DL	Splice-Junctions	Error Rate	7.50%	1992	ScienceDirect	[6]
3.	KBANN	PR+DL	splice-junctions [DNA]	Error Rate	6.4%	1990	Neurips	[84]
4.	FSKBANN	PR+ non-Recursive +DL	Data set from Qian and Sejnowski (1988)	Accuracy	63.4%	1992	ACM	[12]
5.	FSKBANN	PR+ Non-RL+DL	The data set consists of 128 proteins. (85/43) Tarin/Test	Accuracy	61.9%	1991	ScienceDirect	[85]
6.	KBANN	PR +DL	16 in vivo 31P MR spectra	Average Pat / Error	0.1179	1998	Citeseerx	[86]
7.	KBANN	DL/MLP	PE diagnosis dataset	Accuracy	100%	2007	PubMed	[87]
8.	KPNN	DL+UI	TCR dataset	ROC AUC	98.4% (interquartil	2020	PubMed	[88]

					0 404 00			
					e range, 0.979 to 0.987)			
9.	KPANN	DL+UI	Transcriptomic dataset	MAE, Median abs. error	5.51 y, 4.71 y	2021	Nature	[89]
10.	Pathway- Primed	DL+PK	Mouse dataset, Human dataset	Accuracy	0.936	2022	IDUS	[90]
11.	LTN	DL+FOL+FL	Mixed [Neoplasm, Glaucoma]	Accuracy	81-80	2021	IJCLR	[91]
12.	BaLONN	DL+UI	Heart Failure Clinical Records	Tot. PR (%)	69.28%	2021	Europe PMC	[92]
13.	BioBERT+MD Att	DL+MDAtt	BioBERT QA, PubMed QA	Accuracy	84%	2021	Oxford Academic	[93]
14.	MultiPredGO	DL+UI	Protein Sequence	AUC	0.8169	2021	IEEE Xplore	[13]
15.	N/A	ML+SPARQL	GO	ROCAUC	0.79	2017	Oxford Academic	[94]
16.	DeepMiR2GO	DL+UI	miRNA2GO-337	F1-Max	39.90%	2019	MDPI	[14]
17.	SiameseNN (ont)	ML+FOL	PPI Dataset	AUC	0.91%	2021	Oxford Academic	[95]
18.	ExplainDR	DL	IDRiD Dataset	Accuracy	60.19%	2021	CEUR-WS	[15]
19.	RLR	DRL+DR	BIKG Hetionet	MRR	$0.167 \pm .008$	2021	arXiv	[77]
20.	Ne-Sy	DL+UI	Ontologies Dataset	has- indication[{F- Measure}]	72%	2018	CEUR-WS	[78]
21.	Ne-Sy	DL+UI	COVID-19 LUS dataset	MPA	82%	2022	Harvard Press	[74]
22.	N/A	ML+NR	EEG dataset	Accuracy [AVG]- β	68%	2022	ACM	[97]
23.	PP-DKL	DL+PPL	ADNI	MAE[MMSE]	1.36 ± 0.27	2021	Springer	[16]
24.	PoLo	DL+ Logic rules	OREGANO KG	MRR	0.498	2021	Scitepress	[76]
25.	FSD	DL+ Fuzzy Logic	N/A	None	None	2008	Springer	[17]
26.	Neuro-Fuzzy Approaches	Pattern Recognition + UI	FHR Signal	Accelerations Accuracy Decelerations Accuracy	72.60% 65.70%	2002	Springer	[98]
27.	N/A	ML+ Certainty Factor Rules	Aphasia Diagnosis	F-Measure	80%	2019	IEEE	[99]
28.	KGCNN	DL+UI	I2B2-VA challenge dataset	Macro F1 (Intuitive) Micro F1(Intuitive)	0.6760 0.9613	2018	IEEE	[19]
29.	KBANN	DL+PR	vivo 31P MR spectra	ACG Pat/Error (cKBANN-5)	0.1248	1999	IEEE	[100]
30.	EmbedPVP	KG+DL	PAVS database	ROCAUC	0.9960	2024	Oxford Academic	[67]
31.	ChEB-AI	LNN+DL	ChEBI	F1 (micro)	0.9032	2024	RSC	[68]
32.	N/A	DT+DNN	Covid-19 LUS Dataset	Prognostic value (max)	95.00	2023	Elsevier	[69]
33.	NeSyKHG	KHG+DL	Chinese Medical Highorder Relational (CMHR) dataset	Accuracy	0.947	2024	Elsevier	[70]
34.	S-Reinforcement	Subsymbolic+DL	SMILES Data	Reward	9.50	2024	IEEE Xplore	[71]
35.	LNN	Subsymbolic+DL	Mental disorder diagnosis	AUC	0.76	2023	ACL	[72]
36.	ChEBai	Ontology+DL	ChEBI, Tox21	F1 (micro)	0.86	2023	Springer	[73]
37.	STONE	Temporal Logic+DL	CHB-MIT database	F1	0.9834	2022	Elsevier	[75]
38.	NSTSC	Temporal Logic+DL	UCR TIME-SERIES DATA ARCHIVE	Accuracy	84.66	2022	IEEE	[79]
39.	TAM-SenticNet	SenticNet+DL	CLEF eRisk 2022 Lab	F1 score	0.758	2024	Elsevier	[80]
40.	DeepInfusion	Knowledge Extraction + DL	intracranial aneurysms in- house prepared dataset of 409 DSA images	IOU	0.9602	2023	Elsevier	[81]
41.	ELECTRA	Ontology+DL	ChEBI Dataset	F1 Score	0.78	2023	IOS Press	[82]

Note: PR - Propositional Rule; Non-RL - Non-Recursive Rule; UI - Un-identified; MAE - Mean Absolute Error; DR - Deterministic Rules; MRR - Mean Reciprocal Rank; MPA - Mean Prognostic Agreement; NR - Neuroaesthetics Rules; PPL - Probabilistic Programming Languages; ADNI - Alzheimer's Disease Neuroimaging Initiative; Approach - Author does not mention method or model name, thus labeled as an approach; DL - Deep Learning; RL - Reinforcement Learning; FOL - First Order Logic; FL - Fuzzy Logic; ML - Machine Learning; PPI - Protein-Protein Interaction; DRL - Deep Reinforcement Learning; DR - Drug Repurposing; KG - Knowledge Graph; LNN - Logic Neural Network; DT - Decision Tree; DNN - Deep Neural Network; LUS - Lung Ultrasound; AUC - Area Under the Curve; ROC - Receiver Operating Characteristic; ACC - Accuracy.

V. NEURO-SYMBOLIC CHALLENGES

Despite the promise demonstrated by neuro-symbolic (NeSy) approaches in various applications, several critical challenges persist in advancing their use in biomedical contexts, as outlined below.

Knowledge Representation: Encoding biomedical knowledge, such as protein-protein interactions for disease diagnosis, in NeSy models is challenging due to the depth and complexity of information needed for precise clinical applications.

Lack of Standardized Benchmarks & Evaluation: The absence of consistent benchmarks for NeSy systems, like those for drug interaction prediction, hinders the assessment of model efficacy across different healthcare scenarios.

Handling Adversarial Attacks: NeSy models in healthcare, such as those used for diagnostic image analysis, must be resilient against adversarial attacks, which could exploit model vulnerabilities and potentially lead to misdiagnoses.

Common Sense Reasoning: Integrating common sense reasoning, like understanding disease progression stages, is essential for NeSy models to make accurate inferences in complex cases, such as cancer prognosis.KG can be a good candidate to develop robust symbolic engineering.



Fig. 4: Neuro-Symbolic Open Challenges

Integration Complexity: Combining symbolic reasoning and neural networks for medical imaging, like X-ray analysis with rule-based interpretations, is complex and affects model reliability scalability for diverse clinical settings.

Inadequate Explainable and Interpretable Models: In bioactivity prediction for drug development, NeSy models need

to explain why certain compounds are predicted to interact with biological targets. Additionally, inadequate *Explainable notable*.

Scalability Challenges: Scaling NeSy models to handle large genomic datasets, such as genome-wide association studies (GWAS) for disease traits, is difficult since there is a trade-off between accuracy and explainability while maintaining large-scale prediction.

Lack of Comprehensive Model: Existing NeSy models are often limited in scope(lack of regression model) and may struggle to handle the diverse range of tasks needed in healthcare, such as simultaneously predicting drug efficacy and toxicity.

Reasoning Under Uncertainty: In clinical decision support systems, NeSy models must make predictions with uncertain or incomplete patient data, such as when predicting outcomes for rare diseases.

Domain Expertise: Building NeSy models for fields like personalized medicine requires high domain expertise, especially when interpreting complex genomic and phenotypic data.

VI. FUTURE DIRECTION AND OPEN PROBLEM

We propose future research directions building upon the current findings to address existing limitations and further enhance the potential of neuro-symbolic models in biomedical applications, such as:

A. Proposed Novel Approach (LTN-CPI) Using Chemical, Protein Language, and LTN Models for Compound-Protein Interaction (CPI) prediction:

Protein-based therapeutics have emerged as one of the most rapidly advancing sectors within the pharmaceutical industry, driving transformative paradigms in disease treatment. There was an anticipated to account for half of the top ten best-selling drugs globally [198] based on targeting protein. Classical therapeutic drug targets are predominantly concentrated within approximately 130 protein families [199], and the therapeutic protein market has surpassed a valuation of USD 380 billion [200]. Given their significance, studying drug/compound and protein interactions is critical. Research in Compound-Protein Interactions (CPI) or Drug-Target Interactions (DTI) has been mainly instrumental, contributing to substantial advancements in this field [201]. We propose a new reasoning-capable approach for CPI use cases that can be accomplished in breast cancer or any inhibitor- or no-inhibitor-based CPI prediction task.

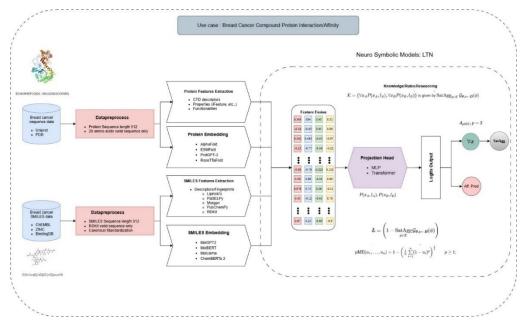


Fig. 5: Approach Proposed (LTN-CPI) Using Chemical, Protein Language, and LTN for Compound-Protein Interaction (CPI) Prediction

Table 7 illustrates the rules, learning, and loss according to LTN constructions in the CPI/DTI task context. The proposed approaches can be experimented with utilizing BindingDB, DAVIS, and KIBA benchmarks from the TDC Drug Target Interaction (DTI) porch.

Contents	Classification
Define Axioms	 \(\forall \times_A, p(\times_A, l_A): \text{ all the examples of class } A(Active/Postive = 0)\text{ should have a label } l_A\) \(\forall x_B, p(x_B, l_B): \text{ all the examples of class } B \text{ (Inactive/Negative = 1) should have a label } l_B\)
Axioms (rules, knowledge base)	$\mathcal{K} = \forall x_A p(x_A, l_A), \forall x_B p(x_B, l_B)$
SatAgg is given by	$\operatorname{SatAgg}_{\phi \in \mathcal{K}} \mathcal{G}_{\theta, x \leftarrow D}(\phi)$
Learning & Loss	$\boldsymbol{L} = \left(1 - \operatorname{SatAgg}_{\boldsymbol{\theta}, \boldsymbol{x} \leftarrow \boldsymbol{B}}(\boldsymbol{\phi})\right)$

B. Inhibitor Prediction and Bio-Activity Classification Using LTN-Enhanced Transformers:

Logic Tensor Networks (LTN) combined with transformer models can offer enhanced predictive capabilities for chemical classification and bio-activity prediction. This approach could facilitate inhibitor prediction and enable accurate classification of molecular activity based on structural and functional characteristics, benefiting areas like cancer treatment and antimicrobial drug development. The LTN + Transformer model is up-and-coming for applications requiring precise classification and interpretability, such as identifying inhibitors for specific targets in complex biochemical pathways.

C. Developing Explainable Med-VQA for Interpretive Systems in Oncology

In the visual question answering (VQA) context, combining vision-based LLMs with symbolic reasoning can support the development of interpretable systems for the Med-VQA field, such as reasoning explainable prediction of medical imaging. For example, reasoning-capable systems could improve interpretability in triple-negative breast cancer imaging by integrating symbolic frameworks to analyze visual data alongside patient histories. This approach seeks to create a robust reasoning system that can provide explanatory insights, supporting oncologists in diagnosing and strategizing treatments with higher precision.

VII. CONCLUSION

This study explored the transformative potential of Neuro-symbolic AI (NeSy) in the healthcare sector. By integrating the strengths of neural networks with symbolic reasoning, NeSy offers unique attributes, such as enhanced explainability and reasoning. We extensively reviewed 977 original Neuro-symbolic studies and identified significant advancements and applications in healthcare and revealed practical simulation results in drug discovery. Moreover, evaluated 41 promising use cases and applications within the biomedical domain. Significantly, we proposed a novel reasoning-capable architecture for compound and drug interaction tasks by integrating chemical and protein language models with the Logic Tensor Network framework.

Overall, these findings underscore the growing potential of Neuro-symbolic AI to bridge critical gaps in explainability, interpretability, and reasoning in AI applications. Building upon this foundation, AI scientists envision hybridizing symbolism and connectionism, the two foundational paradigms of AI. Such an approach could enable machines to achieve human-like cognitive behaviors, including commonsense reasoning, fostering more transparent, trustworthy, scalable, and robust AI-driven healthcare systems. This advancement has the potential to revolutionize various aspects of healthcare, from drug discovery to patient care, ultimately benefiting the global healthcare community.

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Author contributions

DH conceptualized and wrote the manuscripts. Dr. JC guided, review, and lead the project.

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Availability of data and materials

Procured 977 papers, and 41 healthcare-related articles, tables, and figures can be obtained upon request to mhossai5@uab.edu.

Declarations

Conflict of interest: The authors declare no conflict of interest.

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Consent for publication: The authors consent to the publication of this work.

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APPENDIX A: A VARITY OF NESY DOMAIN AND APPLICATIONS PRESENTED AS BELOW.

Domain Of Application	Model	Reference
	KBANN	GG Towell et al., 1994
	LTN	S Badreddine et al., 2022
	Deepinfusion	I. Abdullah., 2023
Healthcare	ExplainDR	SI Jang et al ., 2021
	NeSyL	N Díaz-Rodríguez et al., 2022
	BioBert+Mt Attention	T. Kang et al ., 2021
	GA-NeSy	KW Park et al ., 2021
Cyber Security	Approach	A Piplai et al ., 2023
	CARS	D Bouneffouf et al ., 2014
	CTR	D Bouneffouf et al ., 2012
Recommendation System	KARF	G Spillo et al ., 2021
	NLQ4Rec	M Wu et al 2024
	LPFR	X Tong et al., 2024
	Approach	Y Zhang et al 2023
Robotics/Automation	Approach	A Gomaa et al., 2023
	Sophia	D Hanson et al., 2020
Smart City	Approach	G Morel et al ., 2021
Information Retrieval	Approach	L Dietz et al., 2023
	Review	K Hamilton et al., 2022
	NMN	J Andreas et al., 2015
	NLProlog	L Weber et al., 2019
NLP	Approach	K Gupta et al., 2021
	PIGLeT	R Zellers et al., 2021
	LNN-El	H Jiang et al., 2021
	NS-VQA	K Yi et al., 2019
	NS-CL	J Mao et al., 2019
	Approach	A Mishra et al., 2024
VQA / Computer Vision	XNM	J Shi et al., 2019
	NS-IL	P Johnston et al., 2023
	Approach	J Park et al., 2022
	TITScore	P Ji et al., 2024
	Approach	N karacapilidis et al., 2024
	LIDA	P Agrawal et al., 2024
Generative AI	Genome	Z Chen et al., 2023
	ContextGPT	L Arrotta et al., 2024

APPENDIX: B

Table: Acronyms and Abbreviations

A A A T	Association for the Advancement of Artificial
AAAI	Intelligence
ACL	Association for Computational Linguistics
AI	Artificial Intelligence
CBR	Case-based reasoning
CNN	Convolutional Neural Network
DL	Deep Learning
GCNN	Graph Convolutional Neural Network
GPT3	Third-generation Generative Pre-trained Transformer
IJCAI	International Joint Conference on Artificial Intelligence
KG	Knowledge Graphs
LNN	Logical Neural Networks
LLM	Large Language Models
LTN	Logic Tensor Network
ML	Machine Learning
MLP	Multilayer Perceptron
NeSy	Neuro-Symbolic AI
NLP	Natural Language Processing
NS-CL	Neuro-Symbolic Concept Learner
NN	Neural Network
OOD	Out-of-distribution
ProbLog	Probabilistic Logic Programming
SOTA	State of the Art
ACM	Association for Computing Machinery
NeurIPS	Conference on Neural Information Processing Systems
IDUS	Institutional Repository of the University of Seville
IJCLR	International Journal of Collaborative Learning
IJCLK	Research
HEALTHINF	International Conference on Health Informatics
ScitePress	Science and Technology Publications
IEEE	Institute of Electrical and Electronics Engineers
RSC	Royal Society of Chemistry
AIP	American Institute of Physics
RQ	Research Question

APPENDIX: C

Table: A List of Neuro-Symbolic Models GitHub Repository

	Model/Algorithm	GitHub Link	Dataset	Data Type	Author
1.	KBANN/KBNN	https://github.com/spacewalk01/deep-logic-learning	Promoter & splice-junction datasets	Tabular	Geoffrey G. Towell
2.	NEFCLASS-J	https://github.com/dhecloud/NEFCLASS	Wisconsin Breast Cancer" (WBC)	Tabular	D. D. Nauck
3.	KPNN	https://github.com/epigen/KPNN	RNA-seq dataset	Tabular	Nikolaus Fortelny
4.	SHERLOCK	https://github.com/sherlock-project/sherlock	UCI Machine Learning Repository	Tabular	Ekaterina
5.	NMN	https://github.com/jacob&reas/nmn2	VOA	Image & Text	Jacob &reas
6.	NeuralLP	https://github.com/fanyangxyz/Neural-LP	WikiMovies, WordNet18, Freebase15K	Tabular	Yang
	DeepProbLog	https://github.com/ML-KULeuven/deepproblog	MNIST	Image	Robin Manhaeve
8.	CommonsenseQA	https://github.com/jonathanherzig/commonsenseqa	DREAM/CommonsenseQA	Text	Kaixin Ma
	ANSNA	https://github.com/patham9/ANSNA	Giuseppe Marra	Text	Patrick Hammer
10.	NLProlog	https://github.com/leonweber/nlprolog	MEDHOP, WIKIHOP	Image	Leon Weber
	NS-CL	https://github.com/kexinyi/ns-vqa	CLEVR	Tabular	Jiayuan Mao
12.	NMLN	https://github.com/GiuseppeMarra/nmln	Nations, Kinship & UMLS, SMOKER	Text	Giuseppe Marra
	CORGI	https://github.com/ForoughA/CORGI	Commonsense Reasoning	Text	Forough Arabshahi1
	DFOL-VQA	https://github.com/microsoft/DFOL-VQA	GQA	Tabular	Saeed Amizadeh
15.	GNS-model	https://github.com/rfeinman/GNS-Modeling	Omniglot dataset	Text	Reuben Feinman
13.	G145-model	https://githdo.com/fichinian/Grv5-wodering	Omnigiot dataset	TCAL	Marc Roig Vilamala,
16.	Hybrid-CEP	https://github.com/KyraStyl/Hybrid_CEP_Engine	Urban Sounds 8	Audio	Harrison Taylor
17.	R3-Transformer	https://github.com/hassanhub/R3Transformer	YouCook2	Tabular	Hassan Akbari
18.	KBQA	https://github.com/svakulenk0/KBQA	QALD - 9/ LC-QuAD 1.0	Text	Pavan Kapanipathi
19.	NeSy XIL	https://github.com/ml-research/NeSyXIL	CLEVR-Hans/ColorMNIST	Image	Wolfgang Stammer
20.	LNN	https://github.com/IBM/LNN	Smokers & friends dataset-LTN, & LUBM	Tabular	Ryan Riegel
21.	NeurASP	https://github.com/azreasoners/NeurASP	[Xu et al., 2018]	Tabular	Zhun Yang
22.	MD-informed	https://github.com/Tian312/MD-Attention	COVID-19 data	Tabular	Tian Kang
23.	GABL	https://github.com/AbductiveLearning/GABL	Synthesized dataset	Tabular	Le-Wen Cai
	RWFN	https://github.com/jyhong0304/SII	PASCAL-Part-dataset, ontologies (WordNet)	object detection image	Jinyung Hong
25.	autoBOT	https://github.com/aiden/autobot		Text	Blaž Škrlj
26.	DPL	https://github.com/travis-ci/dpl	IMDb, Yahoo dataset	Tabular	Hoifung Poon
27.	RNNLOGIC	https://github.com/DeepGraphLearning/RNNLogic	FB15k-237, WN18RR	Tabular	Meng Qu*
28.	COMET	https://github.com/dotnet/Comet	SocialIQa, StoryCS	Tabular	Antoine Bosselut
29.	NSNnet	https://github.com/GuillaumeVW/NSNet	MNIST	Image	Ananye Agarwal
29.	Northet	https://github.com/Guinaume v w/19519ct	PASCAL VOC, PASCAL	Object detection	Francesco
30.	Faster-LTN	https://gitlab.com/grains2/Faster-LTN	PART	image	Manigrasso1
31.	EduCe	https://github.com/magiclen/educe	FB15K-237, Constant, Family-gender, UMLS	Image	Anonymous ACL
32.	CTP	https://github.com/microsoft/CtP	CLUTRR	Tabular	Pasquale Minervini
33.	NEUROSPF	https://github.com/neurospf/neurospf	MNIST	Image	Muhammad Usman
34.	NESTER	https://github.com/tapnair/NESTER	ICFHR'14 CROHME	Image	Paolo Dragone
	NSFR	https://github.com/ml-research/nsfr	2D K&insky patterns & 3D CLEVR-Hans	Image & Text	Hikaru Shindo
36.	HRI	https://github.com/Alvearie/HRI	Visual Genome	Image	Claire Glanois
	PIGLeT	https://github.com/Dervall/Piglet	EXIST		Rowan Zellers
38.	Pix2rule	https://github.com/nuric/pix2rule	Subgraph set isomorphism		Nuri Cingillioglu
39.	Latplan	https://github.com/guicho271828/latplan	Twisted LightsOut		Masataro Asai
40.	NS-Dial	https://github.com/shiquanyang/NS-Dial	MultiWOZ 2.1, SMD	Text	Shiquan Yang
41.	DNR	https://github.com/SkBlaz/DNR	BITCOIN	Tabular	Bla*z Skrlj
	NS-ICP	https://github.com/EdmundYanJ/NS-ICF	,ml-1m, Taobao	Tabular	Wei Zhang
	RETOMATON	https://github.com/neulab/retomaton	WIKITEXT-103, Law-MT	Text	Uri Alon
45.	RETURNATUR	mps.//gmuo.com/neurao/retomaton	WIKITEA 1-105, LdW-WII	ICAL	OH AIUH