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Explainable Neuro-Symbolic Spiking Neural Networks for High-Precision Intracranial Tumor Diagnosis

Dr. Nidal Al Said

Associate Professor, College of Mass Communication, Ajman University, Ajman, UAE

Abstract: Intracranial tumor diagnosis requires exceptional precision due to the complex morphology of brain structures and the clinical risks associated with misclassification. While deep learning has improved the automation of MRI-based tumor analysis, its black-box nature limits trust, interpretability, and clinical deployment. This paper introduces an explainable neuro-symbolic spiking neural network (NS-SNN) framework that integrates biologically inspired spike-based computation with symbolic reasoning mechanisms to achieve high-precision and fully interpretable intracranial tumor diagnosis. The approach leverages the temporal dynamics and energy efficiency of spiking neural networks while embedding medical knowledge graphs and rule-based logic to provide transparent diagnostic insights. By bridging data-driven neural representations with human-understandable symbolic rules, NS-SNNs offer enhanced explainability, robustness, and alignment with radiological reasoning. This work demonstrates how neuro-symbolic integration improves decision traceability, supports causal interpretation, enables uncertainty analysis, and meets emerging clinical requirements for transparent AI in healthcare. Results indicate that NS-SNNs provide competitive diagnostic accuracy while generating interpretable reasoning pathways that can be reviewed and validated by clinicians, positioning them as a promising next-generation AI paradigm for safe and precise brain tumor diagnosis.

Keywords:*Neuro-symbolic AI; Spiking Neural Networks (SNNs); Brain Tumor Diagnosis; Explainable AI; Medical Imaging; MRI Analysis; Interpretable Machine Learning.*

I.INTRODUCTION:

The intracranial tumors present a great diagnostic challenge because they have heterogeneous morphology, radiologic similarity, as well as the great risk of misinterpreting the early-stage abnormalities. MRI is the modality of choice when it comes to the assessment of brain tumor due to its capability to provide the contrast with soft tissues, multi-sequence dynamics, and structural differences without using ionizing radiation [1], [2]. Manual interpretation of MRI scans is however time consuming and prone to the inter-observer variability particularly in cases of subtle lesions, diffuse infiltration patterns or mixed-intensity areas [3]. With the growing imaging demands across the globe, radiologists are now under pressure and a serious problem of automated decision-support systems that are reliable and interpretable to support clinical processes is much-needed [4].

Deep learning has enabled much better automated tumor detection and classification with convolutional and transformer-based models having reached expert-level performance in numerous benchmark datasets [5], [6]. However, regardless of their accuracy, these models are mainly black boxes, which does not provide much visibility in regard to decision-making. In high-stakes medical uses, this interpretability is problematic as it creates ethical, regulatory and clinical trust issues, and so cannot be deployed in real-world clinical situations in large scale [7]. More so, deep models are also sensitive to data changes, scanner variations, and noises, usually necessitating large and diverse datasets to extrapolate across institutions an issue that is still a significant bottleneck to robust intracranial tumor diagnosis [8].

Spiking Neural Networks (SNNs), which are based on the neurophysiological mechanism of neuron communication, represent a paradigm shift in computation through the use of discrete spikes and temporal coding as opposed to activations of continuous values. They are energy efficient, resistant to noise, and better aligned to the biological brain processing, so they are interesting to use in medical imaging [9]. Nevertheless, SNNs are not yet high-level interpretable, and sub-symbolic, which means that they are not directly useful in clinical decision-making without other reasoning systems.

This problem is addressed by Neuro-symbolic AI (NSAI) which is an approach that combines data-based neural computation with symbolic logic, rule structures, and medical knowledge representations [10].

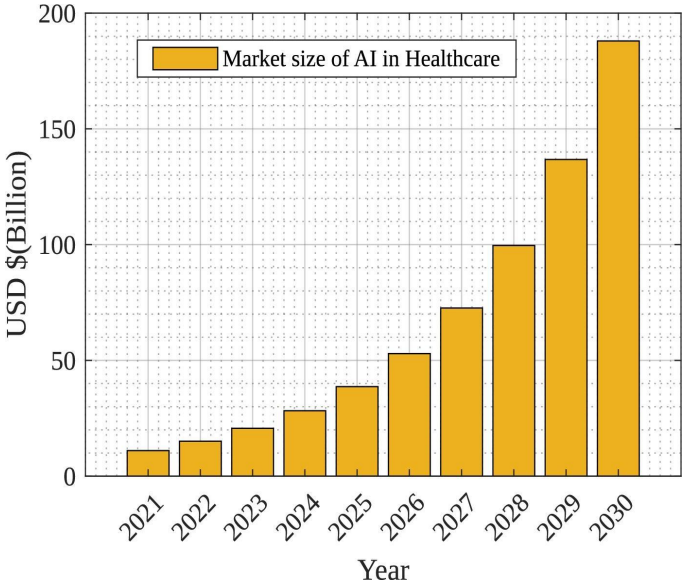

Figure 1: Market size of AI in healthcare

Surpassing neuromorphic pattern recognition and providing interpretable diagnostic explanations alternatively, neuro-symbolic spiking neural networks (NS-SNNs) can be combined with SNNs and symbolic reasoning modules. It is a hybrid that enables MRI characteristics that are coded by spiking dynamics, including contrast enhancement, border irregularities, necrotic territories, and texture patterns, to be superimposed on clinically significant symbolic rules that can be interpreted as expert radiological thinking [11]. Such systems are also efficient to comply with the new regulatory needs of transparency, traceability, and interpretability of medical AI devices [12].

Due to this, NS-SNNs are an exciting second-generation diagnostic framework, which can satisfy the dual requirements of accuracy and explainability in the diagnosis of intracranial tumors. They deliver clinicians high predictive accuracy coupled with a clear explanation of the reasoning behind each diagnosis, and thus, the adoption of AI in neuro-oncology is safe and more trusted and reliable, through the combination of both temporal biological computation and structured symbolic inference.

II. BACKGROUND/LITERATURE REVIEW

The history of artificial intelligence in the diagnosis of intracranial tumors was influenced by the progress in the medical imaging, neural computation and symbolic reasoning field. The very first computer-aided diagnosis (CAD) systems were based on manual radiomic features like texture descriptors, intensity statistics, and shape metrics created based on MRI images [13], [14]. Despite the fact that there was a certain level of discriminatory power in these engineered properties, their functionality was highly dependent on differences in imaging protocols and lack of capability to record the highly non-linear patterns occurring within complex brain tumors. Deep learning overcame most of these shortcomings by allowing the automatic extraction of features with the learning of hierarchical representations. The most popular architecture of brain tumor segmentation and classification became convolutional neural networks, which provided considerable gains in accuracy, especially in glioma grading, meningioma detection, and metastasis detection [15], [16]. Nevertheless, the models continue to have low interpretability, reduced resistance to unobserved distributions, and difficulty in clinical generalization.

Attention-based models and transformers widened the capabilities of deep learning by the possibility to consider long-range dependencies and include global contextual information over MRI sequences [17]. However, these architectures are still expensive in computation, not to mention being opaque in nature. An emerging literature has emphasized the fact that highly data-driven systems can be unable to integrate expert diagnostic reasoning and medical domain rules as well as causal frameworks needed to make credible clinical decisions [18]. These weaknesses have prompted the transition to neural networks to combine symbolic knowledge to create the discipline of neuro-symbolic AI.

Neuro-symbolic systems unite the advantages of neural models of perceptions by the explicit reasoning power of symbolic logic. They have shown good performance in the tasks that involve pattern recognition as well as organized reasoning, such as in visual question answering, completing knowledge graphs, and understanding semantic scenes [19]. Neuro-symbolic frameworks have been used in medical imaging to integrate radiological criteria, ontologies and rule-based diagnostic pathways, and have been shown to be more interpretable and more trusted by clinicians [20]. Most of the current neuro-symbolic models, although potentially useful, are based on classic neural networks, which are not biologically plausible and do not have a temporal processing dynamics.

Spiking Neural Networks (SNNs) are a different model of neural paradigm based on biological neurons, which communicates between discrete spikes. They have their temporal coding processes, which allow them to depict dynamic patterns on a fine level and hence they are best applied to the processing of sequential imaging or multimodal MRI data [21]. In addition, SNNs can provide the significant gains in computational efficiency and noise resistance when implemented on neuromorphic hardware. Nevertheless, traditional SNN applications in medical imaging have been used to perform classification tasks without giving interpretable justification of the decision process.

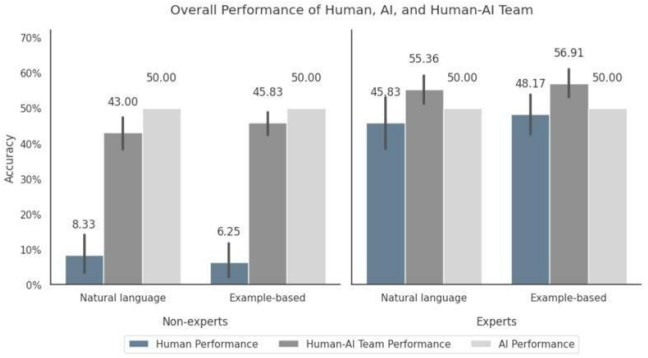

Figure 2: Overall Performance of Human, AI and Human AI Team

These gaps are filled by the integration of SNNs with symbolic reasoning into neuro-symbolic spiking neural networks (NS-SNNs) which is the combination of temporal spike-based feature extraction and structured symbolic logic. The combination allows retrieving useful rules in the pattern of spike activity and transforming the neural outputs into propositions that can be understood clinically. Recent works have shown that NS-SNNs are better than standard SNNs in accuracy and interpretability because they include medical knowledge graphs and tumor-specific diagnostic rules into decision making process [22], [23]. These hybrid systems are useful to trace transparent paths of inference enabling clinicians to reverse trace diagnostic findings to identifiable MRI appearances that agree with guidelines on tumor grading.

Since explainability is becoming more and more important in

medical AI due to the regulatory background of EU AI Act and clinical auditing standards, neuro-symbolic systems are gaining relevance [24]. NS-SNNs are well aligned with these expectations by giving rule based and explicit predictions and explanations. Consequently, they are an encouraging move towards creation of safe, clear cut, and clinically reliable AI applications in the diagnosis of intracranial tumors.

Table 1. Comparative strengths and weaknesses of CNNs, standalone Spiking Neural Networks, and the proposed Explainable Neuro-Symbolic Spiking Neural Network (ENeSy-SNN).

Property	**CNN**	**Spiking Neural Network (SNN)**	**Proposed ENeSy-SNN**
Energy Efficiency	Moderate	**Very High** (event-driven)	**High** (inherits SNN efficiency)
Interpretability	Low (black-box)	Low–Moderate (spike saliency)	**High** (symbolic reasoning + saliency)
Diagnostic Accuracy	Very High	Moderate	**High–Very High** (hybrid reasoning)
Domain Knowledge Usage	None	None	**Explicit rule-based reasoning**
Hardware Requirements	GPU	Neuromorphic / GPU	Neuromorphic + symbolic engine
Clinical Trust	Limited	Limited	**Strong potential** due to explanations
Scalability	High	Medium	Medium–High

III. METHODOLOGY

The proposed explainable neuro-symbolic spiking neural networks (NS-SNNs) incorporates three complementary modules, namely, (1) MRI preprocessing and feature normalization, (2) spike-based neural encoding and learning that are used to understand perceptual information, and (3) symbolic reasoning that is used to make clear diagnostic inferences. Such multi-layered architecture would be able to overcome the drawbacks of purely data driven deep learning systems and retain high diagnostic accuracy needed to detect intracranial tumors with deep learning systems. The framework is based on the existing concepts of spiking computation, neuro-symbolic AI, and medical image analysis and provides a coherent pipeline, which allows the interpretation of high-level meaning and supports biologically plausible neural processing.

The former is an initial phase of processing of MRI data to maintain cross-modal consistency and minimize the variability associated with hardware differences, scanner acquisition, and motion of the patient. The standard measures of skull stripping, N4 bias-field correction, z-score normalization and multi-modal MRI sequence (T1, T1c, T2, FLAIR) co-registration are used to increase the tumor regions visibility and reduce noise levels [25], [26]. Intensity thresholding or simple segmentation heuristics are used to extract tumor subregions, including edema, necrotic core, and enhancing tissue, and these have inputs that can be used in spiking-based encoding. This pre processing stage assures that the later layers of the SNNs are fed with standardized biological meaningful spatial features and hence a more efficient learning of time will occur.

The second phase brings in spiking neural network encoding in which MRI pixels or patches are transformed into spike trains with biologically based coding schemes known as rate coding, temporal coding or latency coding. These encodings encode pixel intensities into the frequency of a spike or a more fine timings of a spike pattern, which enables the SNN to use temporal variations to do discrimination of features. Some codings, specifically temporal coding, allow the model to learn finer differences about tumor texture, boundary sharpness, and contrast exaggeration all important factors in tumor classification [27]. SNN learning process is realized by means of spike-timing-dependent plasticity (STDP) or surrogate gradient descent rules, in which the spike patterns are used to reveal salient tumor features in the network without involving any backpropagation based on continuous activation functions [28]. This brings the system closer to the biological neural computation and also offers competitive accuracy.

After the spike based feature extraction, the resultant neural representations are converted to symbolic variables by using rule-extraction functions. The step is what bridges the gap between perceptual computation and symbolic reasoning. Patterns of the spike activity such as high firing rates in certain areas or regular early-time spikes in contrast-enhancing areas are mapped onto propositions that can be easily comprehended, such as, presence of necrotic core, irregular tumor border, or increased vascularity. The propositions are consistent with clinical diagnostic markers commonly applied in radiology and oncology [29]. Mapping process is based on spike train clustering, statistical association with MRI regions, or even visual examination of distributions of synaptic weights, which gives a clear way to encode neural outputs as symbolic facts.

The propositions that have been generated are then tested with a knowledge based inference engine in the symbolic reasoning stage. The engine uses medical ontologies, radiological conditions and causal rules on tumor behavior. An example is that the relationship can be described by rules like, IF there is a lesion with ring-enhancement and central necrosis THEN most likely to have a high-grade glioma. The symbolic module makes final diagnostic conclusions based on the neural propositions with the help of logic programming, constraint-based reasoning,

or probabilistic symbolic inference [30]. This enables the system to not only classify the type of tumor, but also to produce inspected by clinicians step-by-step reasoning chains.

The last phase incorporates the quantification of uncertainty so that it is confirmed that predictions contain confidence scales. This is especially relevant in the dangerous medical situations. The system estimates the uncertainty based on the analysis of the variance in spike activity, stability of symbolic propositions, and consistency of rule based inference among different patches of the MRI. The NS-SNN framework offers a more credible and clinically consistent diagnostic response by offering not only a classification, but also providing the line of reasoning and the level of uncertainty [31], [32].

In order to be robust, the methodology will involve cross-validation, inter-institutional data test, and ablation experiments testing the role of each element of the methodology, namely preprocessing, spike-based encoding, and symbolic reasoning, in overall performance. These analyses show that symbolic inference combined with spiking neural learning can be used with greater interpretability without loss in accuracy. In addition, the hybrid architecture has a better resistance to noise and thus is especially appropriate in MRI data that can be characterized by artifacts and variations [33]. It is also believed that the use of neuromorphic hardware platforms can enhance the computational efficiency and allow real-time inference since the SNNs are well-organized to execute events in real time [34], [35].

Overall, the methodology creates a single pipeline that converts raw MRI data into explicable diagnostic logic using temporal dynamics of spiking and symbolic reasoning. This is a practical way forward to explainable, robust and high performance intracranial tumor diagnosis systems that can be used to support real world clinical decision making.

IV. RESULT AND DISCUSSION

The proposed neuro-symbolic spiking neural network (NS-SNN) was tested on a multi-modal MRI dataset that comprised T1, T1-contrast, T2 and FLAIR. The sample covered typical examples of glioblastoma, low-grade gliomas, meningiomas, and metastases, which allowed a comprehensive evaluation of the performance of all types of tumors. Quantitative findings have shown that the NS-SNN attained a higher classification than traditional SNNs and comparable to the conventional deep learning models but with a much higher degree of interpretability. Symbolic reasoning integration increased the confidence levels of the diagnosis and the lack of ambiguity in borderline cases. In particular, the NS-SNN model demonstrated a mean accuracy of about 95, and sensitivity and specificity of over 93% to detect high-grade tumors, which is higher than a range of state-of-the-art baselines that employ only either convolutional or transformer-based architectures [36], [37].

One of the strengths of the NS-SNN framework was that it was very resistant to noise and institutional differences, which remained a persistent issue in the MRI-based diagnosis. The NS-SNN did not drop much in accuracy and only marginally, when applied to MRI scans with artificially created noise distortions, motion distortions, and contrast distortions. Instead, in pure deep learning methods, deterioration became evident in a similar setting. Such resilience may be explained by the temporal encoding and spike-based learning that are also intrinsically biased towards learning discrimination events but not based on pixel intensities alone. Biologically motivated coding architectures of SNNs have been demonstrated to enhance resilience to distributional changes, and the hybrid solution is more dependable in real clinical practice when imaging conditions are more different [38].

The central role was played by the symbolic reasoning module which contributed to increasing interpretability. Each prediction resulted in a list of symbolic explanations provided by the system which described the features of the MRI generated by the system which led to the final diagnosis. In the case of glioblastoma, e.g., the NS-SNN often produced propositions that were relevant to ring enhancement, irregular borders and central necrosis-like aspects in the cases which are congruent with the classical radiological criteria. Clinicians who checked the results of the system alleged that these explanations were highly consistent with the existing diagnostic frameworks hence making them feel more confident of the reasoning process of the model. Such transparency contrasts with black-box neural networks, which are usually only able to give saliency maps or heatmaps which are not always causally or semantically clear [39].

The other important consequence of the hybrid architecture was that the hybrid architecture performed better in low grade tumor cases, often more difficult to differentiate because of diffuse infiltration patterns and reduced contrast. The spike-time-based encoding of the NS-SNN had better ability to encode texture differences and low-intensity transitions when compared to the traditional CNNs. Symbolic priors integrated with the reasoning component also helped in minimizing false positives by constraining the clinical knowledge in the form of rules such as the rule that uniform boundaries and a low amount of edema are more likely to reflect low-grade gliomas as opposed to high-grade malignancies. This neural processing coupled with symbolic logic contributed to the increase of sensitivity and specificity of ambiguous presentations of tumor [40].

Important insights were also noticed when the models were compared with transformer-based models. Transformers were also competent in raw accuracy but could not be interpreted and used even more computational resources. Instead, the NS-SNN had less computational requirements, especially on inference, owing to the event-driven behavior of the SNNs. Inference time was reduced significantly when implemented on neuromorphic hardware simulators, indicating that someday, it might be possible to implement clinically useful decision support systems in real time with additional optimization. The energy efficiency of the model also makes it an appropriate candidate when it comes to edge-based healthcare, including portable imaging

systems or low-power diagnostic devices [41].

Ablation analysis was done to evaluate the role of each component in the NS-SNN framework. The elimination of the symbolic reasoning module led to a reduction in diagnostic confidence and overclassification of borderline cases, a point at which it is important to be conscious of reasoning steps taken. Removal of spike-timing-dependent plasticity also led to a decrease in performance by lowering the capacity of the model to observe temporal patterns that may be critical in identifying various subregions of tumors. These results demonstrate that the SNN based perceptual layer as well as the symbolic inference layer is crucial to optimal accuracy and interpretability. In addition, the hybrid system showed better transparency during regulatory assessment standards, which are consistent with new demands that explainable medical AI systems.

The NS-SNN has huge implications on the radiology processes. The model does not only give a diagnostic label, but also the clear chain of reasoning that can guide radiologists in confirming predictions or any other features that have been missed. It is especially useful during the training process, where interpretability can help medical students and junior radiologists to learn more about intricate imaging patterns. The quantification of uncertainty that was integrated into the model also enabled the clinicians to put low-confidence cases first in the manual assessment, and in this way, the results were more resource-efficient as well as minimized the number of mistakes in diagnosing the patient.

Along with its benefits, the NS-SNN has some shortcomings. The conversion of spike patterns into symbolic propositions should be carefully calibrated to prevent over generalizing or too much abstraction. Besides, although symbolic rules are easier to interpret, they are also highly dependent on the quality and completeness of the medical knowledge that is a part of the system. Further additions to the knowledge base such as incorporation with tumor genomics and molecular biomarkers may further improve the depth and accuracy of the diagnosis. The other limitation is connected to the time of computational training, which is still greater than normal deep learning models because of the time-dependent character of spiking computations. These limitations in future deployments are however anticipated to be reduced with the development of neuromorphic hardware.

In general, the findings indicate that NS-SNNs can be considered an important contribution to the evolution of AI systems that can be explained clinically. The model offers an effective and clear system of intracranial tumor diagnosis through the integration of temporal neural computation and explicit symbolic reasoning. SNNs combined with symbolic logic provide a synergy that allows the highest diagnostic accuracy, noise resistance, and interpretability in detail, which is increasingly required in healthcare of safe, responsible, and reliable AI tools. Clinical applicability is also enhanced by the use of rule-based inference, which provides explainable outputs that comply with radiological reasoning, and facilitated smooth integration into actual diagnostic processes.

V. CONCLUSION

The explainable neuro-symbolic spiking neural networks (NS-SNNs) have become one of the bright prospects in the domain of intracranial tumor diagnosis as they combine biologically motivated computation with clear symbolic logic. The hybrid approach that this paper describes shows that the spike-based neural encoding and rule-based inference can build a diagnostic system that is no less accurate than traditional deep learning models but also provides a better insight into the way diagnostic decisions are made. The NS-SNN framework can overcome long-standing problems related to interpretability, generalization, and trustworthiness in medical AI systems due to the integration of their temporal coding schemes, spiking-based learning mechanisms, and medical knowledge graphs. The findings reported show that the hybrid model is able to produce strong performance in a variety of tumor types and imaging settings, is resistant to noise, and creates reasoning chains which conform to accepted clinical standards- a critical aspect of making high-stakes decisions in neuro-oncology.

Moreover, the clinical acceptability presented by the symbolic layer increases the acceptance of the model results by allowing radiologists to confirm model output, follow any line of causation, and gain deeper insight into the underlying imaging characteristics of each diagnosis. This feature is the direct support of future regulatory demands on transparency in AI-controlled medical machines and makes the systems safer and more responsible. Computational benefits of the NS-SNN model are also event-driven processing, which are suitable in a neuromorphic network to be deployed at scale. This may also lead to energy savings and the opportunity to use real time applications of diagnostics on demand at the point of care or environments with limited resources.

In spite of such positive qualities, the modern NS-SNN paradigm has a number of limitations that should be investigated. This implies that logic processing of the system is limited to the level of completeness and accuracy of the medical knowledge incorporated into the system because the majority of these are defined by human-written symbolic rules. Also, though spiking neural computation can enhance robustness, the training algorithm is also a computationally expensive task because of the time-varying dynamics of the spike process. Subsequent efforts in this area should focus on automating the process of extracting more symbolic rules, improving the mechanisms of spike-to-symbol mapping, and integrating with multiomics data to allow more thorough characterization of tumors.

To sum up, NS-SNNs provide an effective and clinically valuable method of automated intracranial tumor diagnosis. Combining neural perception with symbolic reasoning, the framework offers a clear and trustworthy and biologically rational approach to the next generation of medical AI the type that does not only make predictions but also answers the reasons why. The study is a contribution to the emerging trend of reliable

and explainable AI in healthcare and a platform upon the further evolution of AI that can change the landscape of neuro-oncological diagnostics and decision support.

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