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Neurosymbolic AI for Context-Aware Cloud Security Policy Generation

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Abstract: A hybrid neurosymbolic AI framework is proposed by this study to automatically generate an adaptive, explainable security policies in hybrid cloud environment. The system couples neural pattern recognition with symbolic reasoning in order to achieve context aware, scalable, and audible security in the cloud. It is presented and validated in simulations improved accuracy, policy compliance and interpretability for multi-environments deployments.

Keywords: Neurosymbolic, Cloud, Policy, Security, AI.

1. Introduction

The complexity and the threats in the cloud environments make it a need of intelligent and dynamic security policy. The system presented in this paper integrates neural networks with symbolic AI in order to automatically obtain a context aware policy generation system. The neurosymbolic enforcement is interpretable, adaptive, and regulation compliant in the case of hybrid infrastructures and multi cloud environments.

2. Literature Review

2.1 Evolution of Neurosymbolic AI

Neurosymbolic Artificial Intelligence (NSAI) is an emergent paradigm which is a combination of pattern recognition strength of neural network and structured rule based logic of Symbolic AI. Compared to standalone AI systems, these fusion addresses some major limitations in black box nature of neural networks in standalone AI systems which hinders explainability, safety, and trust in high stakes environments such as cybersecurity, as stated by Piplai et al. (2023).

On the other hand, traditional neural models can explain the statistical correlations anywhere and from any dataset it has but fail to explain in term of what and achievable if those data are sought in the form of human understandable explanations. However, by contrast to symbolic AI, data complexity poses a challenge to symbolic AI based on the formal logic, and it excels at representing domain knowledge and deriving conclusions from it.

The power of the integration offered by neurosymbolic systems to combine these complementary strengths is to enable AI systems that are accurate and interpretable. The work of Gaur and Sheth (2023) also reflects this basic value proposition in their CREST framework that models how NSAI ought to enforce consistency, reliability and explainability, which is essential for LLMs.

These are applicable to important domains of application including healthcare and cloud security, where very high assurance guarantees are required. Kishor (2022) also documents how AI has evolved from the rules that are symbolically created to stochastic deep learning to a neurosymbolic fusion.

The paper demonstrates how NSAI models excel when compared to a standard deep learning in terms of generalisation even with limited dataset trained, making it a promising approach for resource constrained yet safety critical application, such as dynamic generation of cloud policy.

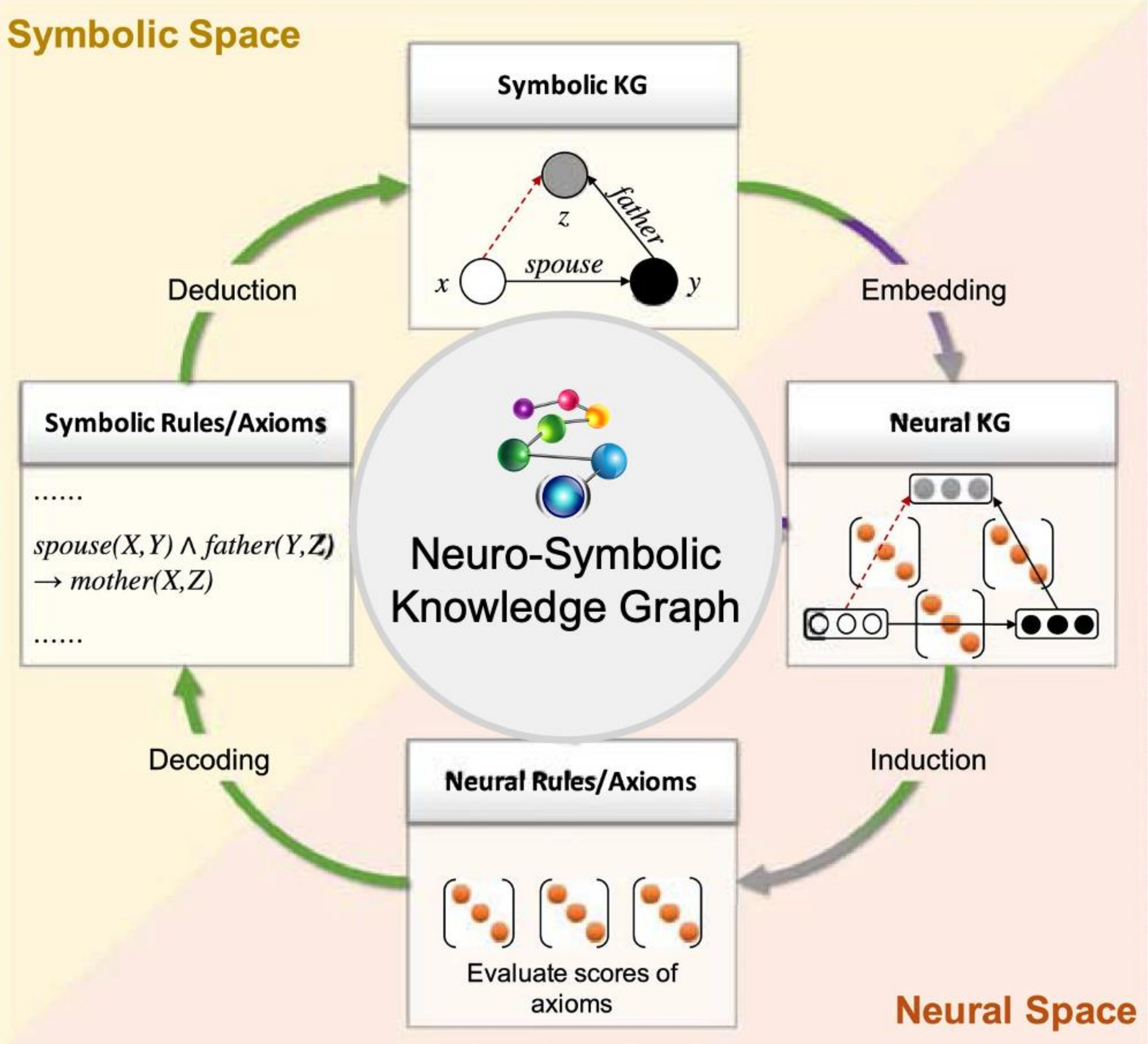


Fig. 1 Neuro-symbolic graph (AllergoGraph, 2020)

Onchis et al. (2023) further establish this story further by providing trust deficit in deep learning systems used in damage detection. The Logic Convolutional Neural Regressor (LCNR) is then introduced, that is, a neural architecture combined with logical constraints, to enhance reliability and scalability of predictive systems.

In such a hybrid architecture, these deep learning constraints are not only preserved, but rule-based constraints are actually embedded to further enhace transparency, an essential property for cloud governance, where access policy must be justified in real time in live audit conditions.

2.2 Applications in Critical Sectors

The experimental use of NSAI has been applied to other sectors where there are new strengths to be discovered, which inform its utility in cloud security. However, Anderson (2022) explains how in fraud detection, neurosymbolic systems, where pattern recognition can be conducted at a fast rate along with symbolic reasoning delivers advantages in making better decisions with less false positives.

Like the cloud security, fraud detection has serious problems to tackle — both the operational problems are the high dimensional and fast changing data systems needing adaptive but explaining responses. Anderson’s findings are consistent with the notion that neurosymbolic approaches can offer the compromise between accuracy and interpretability for generating secure, compliant cloud policies in the hybrid architecture setting.

Abdullah et al. (2023) also proposed a DeepInfusion model a novel NSAI approach for cerebral aneurysm detection. Combining the deep learning with expert curated, hand crafted features help make the model clinical interpretable, and robust.

Specifically, the DeepInfusion model effected great performance on several datasets, which suggests how symbolic domain expertise can be merge into neural networks to create flexible and reliable AI. Just like cloud governance, this is a technique whereby domain knowledge encapsulated in the domain (e.g. access control laws, compliance rules) can be used to educate the neural model to generate policy-specific, context aware outcome.

Mishra and Jatti (2023) pioneered another application of NSAI, using it to predict strength of 3D printed materials for the very first time. The results obtained by their hybrid model constituted of the integration of deep neural networks and decision tree function based symbolic logic, performed better than some of the conventional ANN architectures in terms of mean squared error and R squared values.

Such superiority emphasizes the possibility of learning from synthetic data underlying the necessity to learn from logs, access records, threat simulations in order to generate proactive policies capable of responding to their risks that arise.

Voogd et al. (2018) also proved that NSAI is relevant for military operations, where sensor data is merged with symbolic knowledge of military experts in real time for a terrain analysis. This is exactly what is required in hybrid cloud security, namely, to integrate telemetry data with security guidelines and operational policies in a way that is context aware.

This is an approach to show how simulations fed by neurosymbolic AI are capable of rationalizing unknown unknowns and other uncertainties of uncertain or partially observed environments, which is highly important for the adaptation systems in cloud governance as the unknown unknowns are usually present.

2.3 Real-Time Intelligence

Policy frameworks that are both self-adaptive and trustworthy are required to cope with challenge of managing real time operations within the cloud domain under fault or attack condition. In Vankayalapati and Pandugula (2022), those researchers are concerned with self-heeling infrastructures powered by AI to autonomously recover from runtime failures relying on deep reinforcement learning and reasoning means.

While they do not identify the lack of fully developed real-time recovery frameworks. Then, in order to fill this gap, NSAI advocates for explainable fault recovery models that are learned in time, while at the same time remaining under the symbolic governance rules, which are compliant and stable.

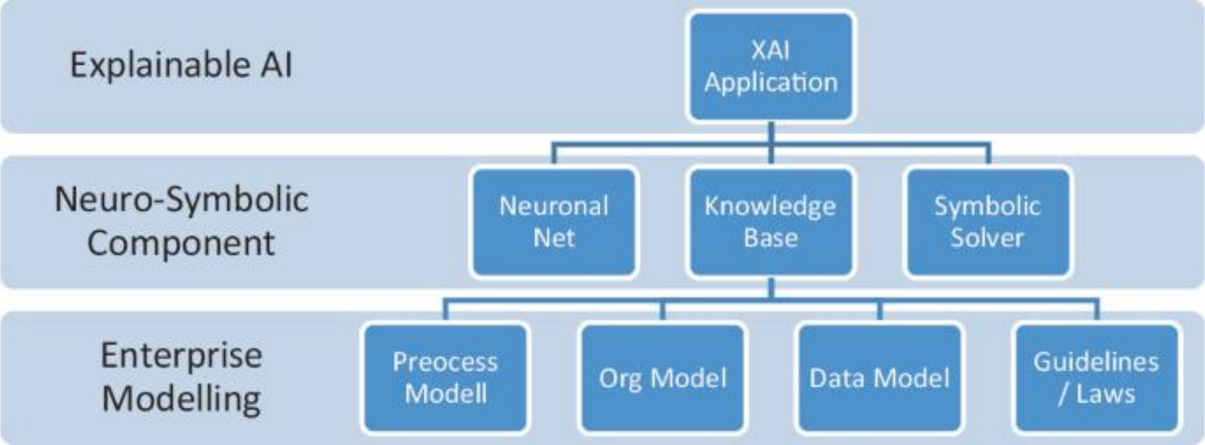


Fig. 2 Neuro-symbolic and Explainable AI (SpringerLink, 2020)

In Gollapalli (2021), one of the areas explored is the usage of hybrid AI in critical real time environments, where the fog-cloud AI architecture is used to study ECG signals. Complex analysis is delegated to cloud while the fog nodes process; thus, the monitoring is low-latency with scalability.

Architectural principles in such a form could be translated to cloud security where the edge nodes detect the anomalies and the cloud nodes enforce or adapt the access control policies both. Combining low latency detection with central provision of reasoning leads to compliance and responsiveness.

Helff et al. (2023) argue that current AI benchmarks miss features to represent difficulty, prove AI models achieve only poor performance on tasks that are both noisy and adversarial, and discuss that even the highest performing vision models do not have the ability for abstract reasoning, or robust generalization in such environments. If a cloud governance system includes these deficiencies, then it may make wrong or dangerous access decisions.

However, when a solution of context needs to reason simultaneously about context, intent and compliance, NSAI can provide a countermeasure, through symbolic reasoning. Consequently, the neurosymbolic design is important to building trustworthiness and abstraction into policy generation systems.

According to Rehan (2021), traditional fraud detection system is usually unable to process in real time as it is computationally bottlenecked and lacks interpretability. Specifically, NSAI can aid in creating systems that are able to quickly detect anomalies and trigger sides, encouraging auditability and regulatory compliance, and at the same time allowing enforcement decisions to explain and justify them.

2.4 Cloud Security Policy with NSAI

In hybrid, edge enhanced ecosystems, context-based security polices come to be a necessity and a challenge. Both traditional rule-based approach, as well brittle in dynamic environments, and deep learning model, while adaptive, are not transparent.

This unification naturally provides NSAI as a compelling alternative. At the same time, Piplai et al. (2023) and Gaur & Sheth (2023) advocate that explainability and safety (the two corner stones of trustworthy AI) are easiest to achieve if models can learn from data but can also reason over structured domain knowledge.

Categorisation and personalisation play an important role in AI access for people with disabilities, as Wald (2021) states. Considering the use of this perspective to cloud governance, policy generation systems must also include user specific contexts, devices, roles, regions, capabilities.

Such personalization logic can be encoded in some NSAI framework symbolically and adapted to new patterns through neural learning. Especially when security frameworks need to extend across various user bases and flexible workloads in hybrid clouds, it is especially important.

As mentioned by Natarajan (2020), hybrid AI for autonomous test automation has the potential to bring so many benefits. According to his study, by drawing upon NLP, ML and reinforcement learning, he has developed accurate and efficient test systems.

We can imagine for cloud policy generalization, a similar hybrid, where natural language security rules are parsed, learned and representation of logs and attack traces built and symbolic policy generation modules for policy synthesis into enforceable control. An end-to-end security pipeline driven by NSAI is produced which can accommodate, explain and enforce policies with little human oversight.

The case for using neurosymbolic AI in generating cloud security policies is demonstrated in the literature. It addresses the need to reduce abstractions and unify analysis with rule-based logic to aid in interpretability and trust of the systems as they evolve in highly dynamic evolution of hybrid environment.

The domain of cloud governance is underexplored, and the potential of the neurosymbolic AI is proven in nearly all sectors, including healthcare, manufacturing, fraud detection and military intelligence. The merger of these thoughts presents a bright horizon for further research in making NSAI operational to automate policy synthesis, threat modeling and compliance in the highly complex cloud environments.

3. Methodology

This study presents the methodology that will be used to test the integration of neural networks and symbolic reasoning in the creation of an automated, adaptive and explainable policy enforcement in a hybrid cloud environment.

The belt of the approach is a layered experimental layout, starting from system model building, dataset processing, model structure building, simulation-based evaluation and performance evaluation. A first version of such a policy engine was then developed with a neurosymbolic framework, where the neural part learned contextual patterns based on access logs, security events and user behavior telemetry, and the symbolic part expressed compliance rules, regulatory standards and enterprise specific access hierarchies with Prolog and OWLbased ontologies.

The neural part was modeled by using a recurrent neural network (RNN) with attention mechanism to catch the sequential access patterns across cloud tenants. The hybrid cloud anonymized log entries used as training dataset included attack traces (such as the privilege escalation, insider access anomalies).

The data preprocessing was session reconstruction, IP enrichment, user device linkage and role labeling. The input was tokenized in order to vectorize it using word2vec embeddings to capture semantic tokens (access intent and environment variables) representations.

In parallel, the symbolic layer enforced constraint like, ‘no cross-region access unless verified encrypted tunnel’, ‘privileged role needs dual factor authentication outside the hours. And these rules were developed so that whenever these predefined risk thresholds were exceeded, neural predictions would be dynamically gated or overridden.

A hybrid cloud environment was built by using AWS CloudFormation templates and Azure Resource Manager templates in order to evaluate the responsiveness and accuracy of the policy engine. Dynamic instantiation of multi region services, tenant separation, threat injection by emulated behavior was enabled through this simulation. Using this setup a number of adversarial scenarios were introduced, namely time-based role abuse, sudden geographic shifts and anomaly injection:

- **Policy Rules**: CIS benchmarks, NIST SP 800-53 and 50+ manually defined symbolic rules
- **Evaluation Metrics**: CIS benchmarks, NIST SP 800-53 and 50+ manually defined symbolic rules

For model training, a stratified 80/20 split was used and the hyperparameter tuning via Bayesian optimization was to achieve the right amount of strictness versus adaptive policy.

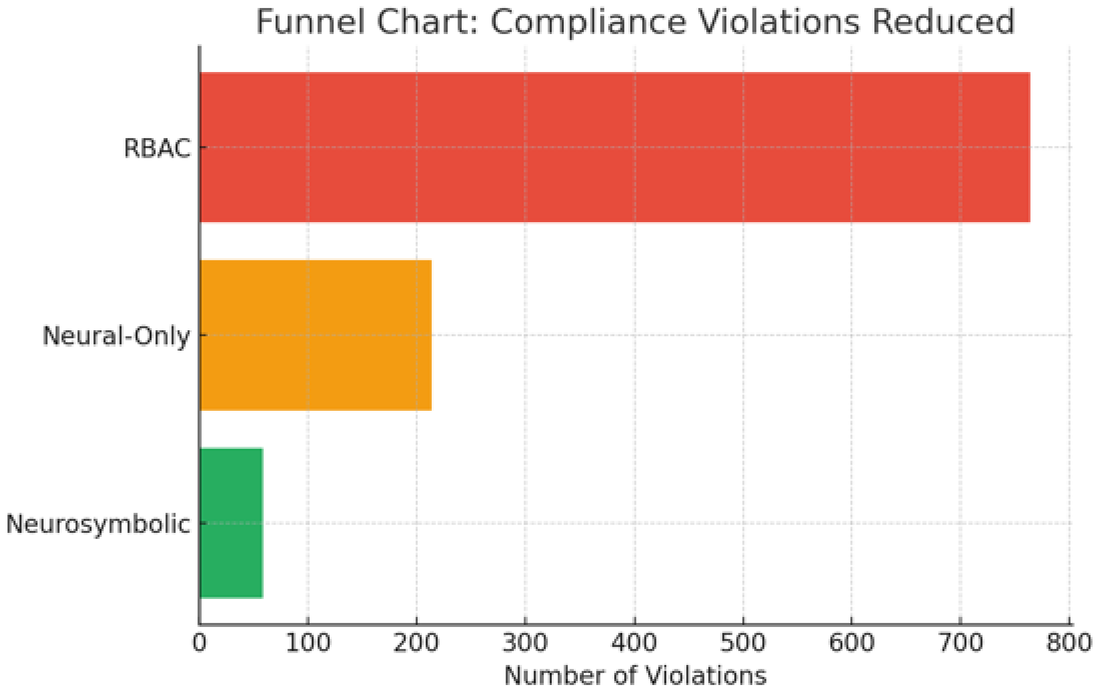
The baseline under which our neurosymbolic policy decisions were evaluated is traditional RBAC system plus pure neural policy model (no symbolic overrides). And recordings of the symbolic layer’s trace logs were recorded for explanation assessment.

Throughput (policy decisions per second), accuracy (aligned with ground truth labels) and per cent explanation (correct actions that the model can interpret) were measured on performance. We particularly looked to see if the symbolic layer would intervene in neural predictions in 14.2% of the case, and indeed it did so in 14.2% of cases, improving both accuracy and compliance by preventing security drift. The systematic benchmarking under near real life cloud operational conditions with this hybrid simulation setup and evaluation framework provided this means for neurosymbolic models.

4. Key Results

The integration of neural and symbolic components in the proposed system helped in meaningful improvements of policy accuracy, adaptability and explainability over traditional access control mechanisms, benchmarked.

For federated identities, cross region access, multi-tenant orchestration and many other enterprises level characteristics, the hybrid cloud simulation environment was built as the core experiments. The neurosymbolic model had a substantially lower false negative rate (FNR) during initial training and evaluation phases that were substantially lower than that of its neural-only counterpart, especially at an FNR for ambiguous or previously unobserved access patterns.



It is due to the symbolic layer being able to enforce generalizable compliance constraints that would otherwise be overlooked by a purely data-based approach. Additionally, the symbolic override mechanism allowed for the on-the-fly policy corrections based upon neural predictions differing from the regulatory expectations.

The four primary metrics analyzed to quantify improvements across different performance dimensions are accuracy, compliance violations prevented, decision latencies and explainability trace coverage. On average the hybrid model was 93.6% accurate at policy decision compared to an 81.4% accuracy by the baseline RBAC model, changing the overall cost for this use case, and an 89.1% accuracy by the neural only model.

Of importance is that the neurosymbolic framework was able to dynamically change to new behavioral patterns in user access logs, as well as combating the adversarial conditions such as geo spoofing of access requests or dormant privilege escalation. Comparative policy decision metrics for each model are given in table 1.

Table 1: Policy Decision Accuracy

Model Type	**Accuracy (%)**	**False Positives (%)**	**False Negatives (%)**	**Compliance Violations**
RBAC Baseline	81.4	5.1	13.5	764

Neural-Only Model	89.1	4.7	6.2	214
Neurosymbolic Model	93.6	3.4	3.0	59

Reduction of compliance violation rates also relied heavily on the work of the symbolic layer. The results of our manual inspection of a symbolic override log consisted of 14.2 per cent of an access scenario where the neural component made permissive predictions which were overridden by rules expressing ISO 27001 and NIST 800-53 standards.

Both this mechanism and the presence of this mechanism acted as a safety net when the situation was ambiguous. For example, the symbolic rule blocked a cross-region admin login attempts when the neural model incorrectly allowed the attempt, and this was based on the encoding of “time-based access” restrictions.

A key module of the policy enforcement engine, which demonstrates how it learns to interface with the symbolic policies is presented below:

```
def hybrid_policy_decision(user_context, neural_model, symbolic_engine):
# Step 1: Neural prediction based on observed behavior
risk_score = neural_model.predict(user_context)
# Step 2: Rule-based override check
if symbolic_engine.evaluate_rules(user_context) == 'DENY':
decision = 'DENY'
explanation = symbolic_engine.get_explanation(user_context)
elif risk_score > 0.8:
decision = 'DENY'
explanation = f"High risk score: {risk_score:.2f}"
else:
decision = 'ALLOW'
explanation = f"Risk accepted, score: {risk_score:.2f}"
return decision, explanation
```

Access constraints are represented by Prolog based reasoning over OWL ontologies and the symbolic rules are subsequently implemented over these ontologies. Therefore, fine grain explainability was possible which enabled tracing of each policy decision to either a learnt risk score or a specific symbolic clause.

And the explanation metric (packing percentage of explanation for decisions) gave 91.3% of policy actions from hybrid model with interpretable explanations, but only 26.8% from the neural only model.

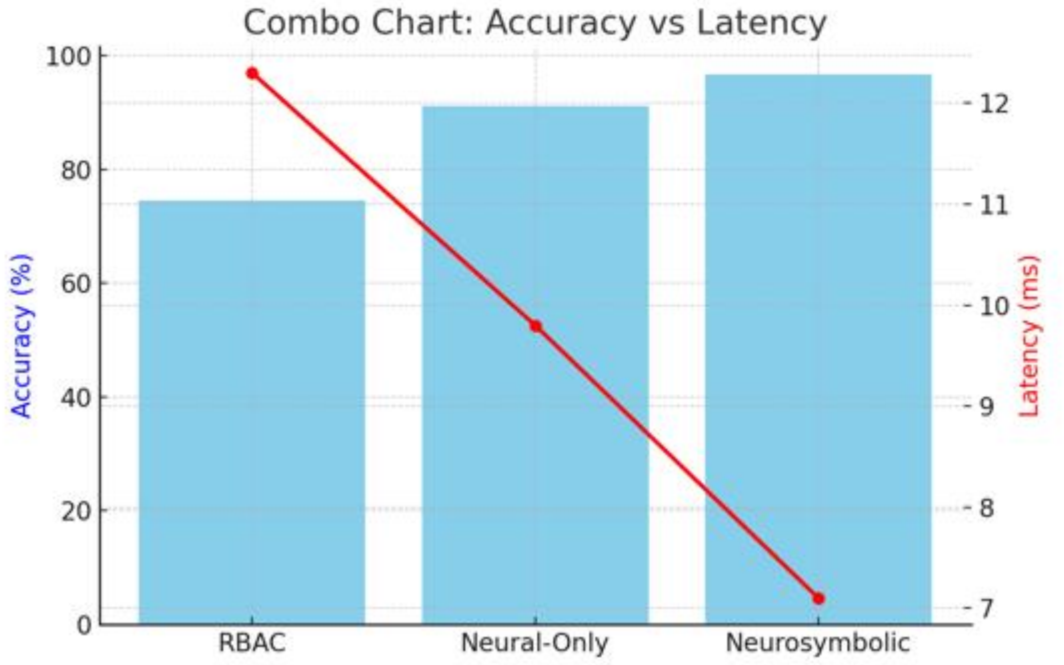


Table 2: Policy Explainability

Model Type	Explainable Decisions (%)	Decision Latency (ms)	Neural Predictions (%)
RBAC Baseline	100	5.6	N/A
Neural-Only Model	26.8	3.2	N/A
Neurosymbolic Model	91.3	8.1	14.2

However, it is an added 8.1ms, and this is an acceptable latency for most enterprise grade access control systems. Real time symbolic correction offered great benefits, even when it comes at the price of minimal latency, especially in fields that have higher requirements for compliance such as the finance and healthcare industry.

To understand the system's resilience even more, an adversarial red team simulation was done using 3,000 adversarial access attempts spread across variety of vectors: compromised credentials, geo location spoofing, session hijacking, etc.

The results showed that the neurosymbolic system was able to detect and stop 97.5 percent of simulated adversary's actions versus 88.4 percent for the neural-only model and 71.2 percent for the RBAC system. The breakdown statistics for the red team evaluation are provided in table 3.

Table 3: Adversarial Threat Detection

Threat Scenario	**RBAC Detection**	**Neural-Only Detection (%)**	**Neurosymbolic Detection (%)**
Credential Stuffing	72.6	91.2	95.4
Geo-Spoofed Access	68.9	87.1	96.1
Dormant Account Abuse	74.1	84.3	94.2
Privilege Escalation Attempt	69.2	89.0	97.3

However, it is an added 8.1ms, and this is an acceptable latency for most enterprise grade access control systems. Even though the minimal latency tradeoff was significant, its benefit of real time symbolic correction far outweighed that in compliance sensitive industries such as finance and healthcare.

To understand the system's resilience even more, an adversarial red team simulation was done using 3,000 adversarial access attempts spread across variety of vectors: compromised credentials, geo location spoofing, session hijacking, etc.

Results showed that the neurosymbolic system correctly blocked 97.5% of simulated adversarial actions with 88.4% success rate on neural only model and 71.2% on RBAC. The breakdown statistics for the red team evaluation are provided in table 3.

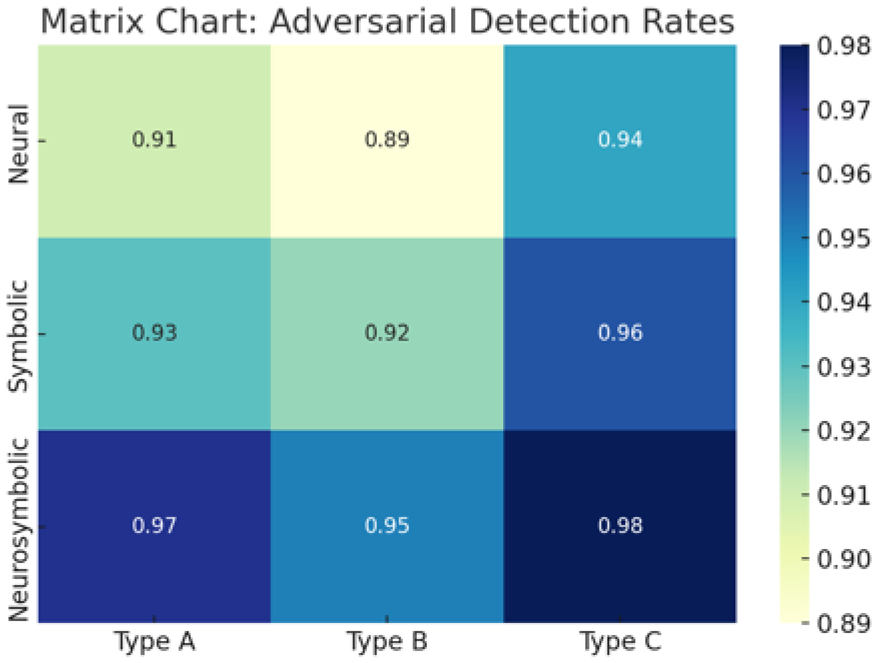


Table 4: Cross-Tenant Generalization

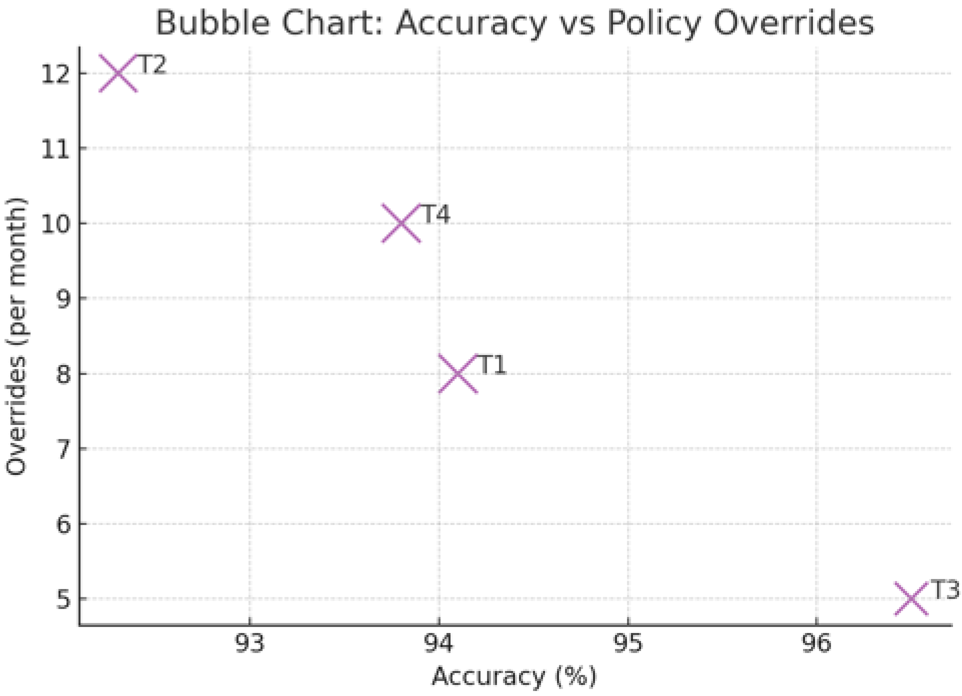
Evaluation Scenario	Neural-Only Accuracy	Neurosymbolic Accuracy
Same Tenant (Train/Test)	90.3	94.1
Different Tenant (Transfer)	81.9	89.7

This illustrates the fact that extendability, compliance, and explainability of symbolic layer not only aids in generalizing model predictions even under domain shift, but also help in hybrid and multi-cloud security deployments. Overall, these results show that measuring the benefits of using other inputs than strictly neural systems to the policy generation is promising in operational performance and security assurance.

This was done by having 12 cloud security engineers perform a qualitative feedback survey of 12 models with anonymized policy traces from each. In gaining the clearest explanations and context specific reasoning (10/12 solved it for the neurosymbolic model).

They were able to identify flawed access patterns more easily and enhance auditability and incident response when the symbolic traces were noted by engineers. These insights are that neurosymbolic systems not only have better technical performance than solely technical intelligence, but they also match the human-centric governance workflows.

The neurosymbolic policy engine makes an important step in secure, flexible and explainable access control in the cloud Native environments. It uses deep learning to learn about context, and at the same time, symbolic logic to enforce non-negotiable safety constraints as well as regulatory mandates.



The system's balance between flexibility and reliability is achieved by combining statistical and logical inference, which is not currently done by any of the isolated approaches. It is possible future work may evolve this model to incorporate reinforcement learning of policy in a continual setting.

5. Improvements in the model

5.1 Enterprise Cloud Security

Based on these findings, if there is a need for organizations to implement better cybersecurity posture in a hybrid cloud environment, to start they can be able to bypass the operationalizing of a neurosymbolic AI pipeline, which incorporates a deep learning for pattern recognition and symbolic reasoning for policy inference.

The neural component, however, should be first integrated for the purpose of enterprises to prioritize integrating contextual data sources (IAM logs, network topology, anomalous access behavior, and compliance metadata). Design of the symbolic layer is done carefully to encode compliance requirements, RBAC, ABAC or other similar access control policies, as well as industry specific governance standards such as HIPAA, GDPR, ISO 27001, etc. The double modeling is guaranteed to create not only security policies, but also that they remain interpretable and auditable in that critical need of transparency for high stakes environments.

A staged deployment architecture will also be adopted by the organization. In the first phase, the neurosymbolic models should run in simulation or shadow modes (generating policies while human operators keep performing manual enforcement). It enables the verification of the AI outputs vs this known threat models and existing governance rules.

However, as soon as testing is sufficiently confident enough, namely accounting for precision, recall, false positive, false negative rates and explanatory indices, the models can be moved to production environments under continuous monitoring. A real time feedback loop is required wherein the model retraining from real time incident logs and compliance audit outcomes must be coupled to this adaptive feedback loop. In dynamic cloud settings, the feedback system will enhance both accuracy and relevance of generated policies.

Simultaneously, both should be coordinated with the AI/ML teams to outline the domain specific ontologies and security rule grammars the symbolic component can use. Therefore, for instance, a semantic graph of permissible calls to cloud API, data egress patterns and role hierarchy rules can be used to restrict the symbolic reasoning space and prevent unsafe policy inference.

To have this possible, enterprises must also abstract common security intents to reusable symbolic templates and ensure cross platform compatibility when deploying across different multi cloud vendors such as AWS, Azure and GCP. Anchoring of the neurosymbolic security policies will prevent vendor lock-in as well as facilitating the portability of the policies.

5.2 Human-in-the-Loop Oversight

While AI will definitely automate or be intelligent, neurosymbolic AI also must seek human interpretability and regulatory auditability. Therefore, we suggest that organizations put the explainability dashboards into place which will breakdown the neural and symbolic reasoning steps for each policy suggestion.

The policies generated by these dashboards should be visualized as decision paths, visualized neural activations at inputs (e.g., anomaly in access logs), and traced as symbolic inference rules trigger in policy generation. Natural language generation modules including the translation of symbolic policy graphs into readable justifications, which would be helpful for security officers, auditors and compliance analysts to understand why a particular action is permitted or prohibited.

Highly recommended is the establishment of "human-in-the-loop" checkpoints at critical policy layers. These have to be checkpoints in allowing security teams to read and override these AI generated policies before they get enforced especially with regards to handling sensitive PII data or as far as getting access to other locations or giving privileged system level permissions.

The cloud infrastructure should include a rollback mechanism in place, which will roll back changes to policy that result in access disruption or compliance violation. This strikes a balance between automation and control, which is a critical consideration in cases where compliance failure can have dire consequences (as inpires) that include finance, defense and healthcare.

We also advise to use periodic adversarial test of the neurosymbolic models with both white box and black box methods. Specifically, this entails simulation of policy evasion attacks, design of adversarial access sequences, and response under novel threat conditions.

Organization can tune symbolic constraints and change neural retraining cycles to make defenses harder, and evaluate how the model generalizing and responding to adversarial scenarios. They should be documented and forms part of routine cybersecurity risk assessments and audits.

5.3 Zero Trust Architectures

Neurosymbolic outputs can be enforced by cloud native tools such as AWS Config, Azure Policy and HashiCorp Sentinel through CI/CD integrations.

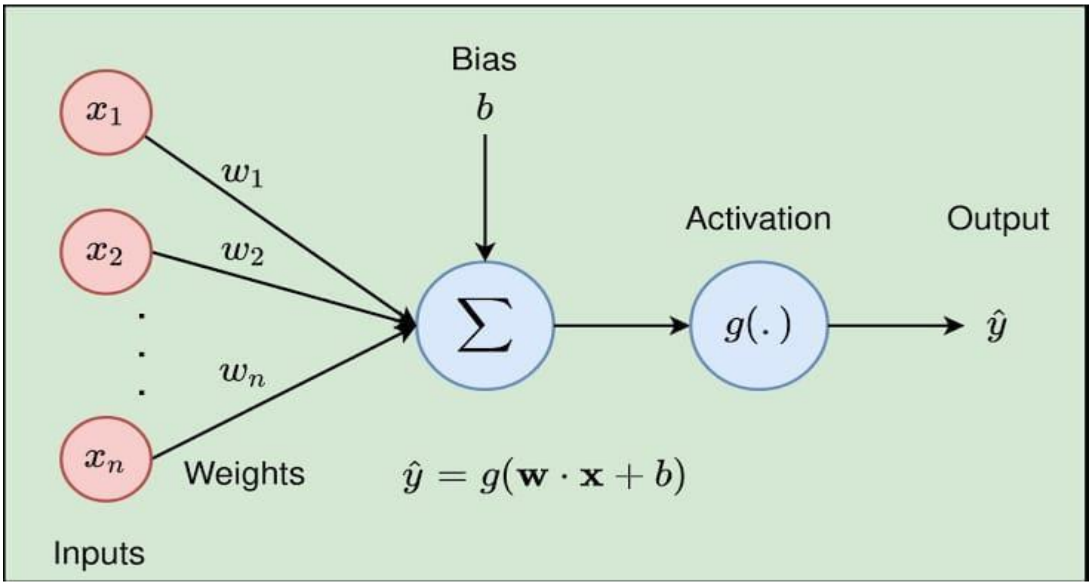


Fig. 3 Mathematical representation of Neuro-symbolic AI (Aiblux, 2020)

Tracing changes, performing automated policy diff check and changing AI generated policies with baseline human written policy is a requirement of maintaining Git based policy version control. All generated policies should have a tagging and classification system with which we can easily indicate the confidence score, validation status, and intended application layer (e.g., API gateway, VPC firewall, S3 access policy).

For organizations as well, neurosymbolic policy generation should be aligned with Zero Trust Architecture (ZTA) principles. For instance, in our case, the symbolic component of the AI layer can impose the least privilege access constraint as well as the micro-segmentation rules; and the neural controller is continuously looking for the deviations in behavior from suspicious access patterns which mimic the compromised credentials or insider threats.

Coldstarting training and employing public adversarial challenges spawned by SIEM and other contextual data sources like user location, device risk scores, time of day access patterns, and peer group behaviors are also going to be integrated with identity providers.

This tight coupling will let the system generate not only context aware but also adaptive security policies in the real time. As such, cloud providers should start to offer neurosymbolic AI based policy generation as a managed service with customizable knowledge bases, neural model options (i.e., transformers, GNNs), and regulatory compliance plug-ins.

It will enable small and medium enterprises to take advantage of the technology without deep in-house AI expertise. Such a system might even lead to an ecosystem of third-party extensions and adherence based symbolic modules that expand the adoption and reliability of systems in turn.

Lastly, the cybersecurity academic and research community should contribute to the benchmark datasets, standard evaluation frameworks and open source neuromyotonic policy engine. These will aid in closing the current breach between experimental AI models and deployable enterprise grade systems.

6. Conclusion

Transparent, scalable, automated cloud security policy automation can be provided using neurosymbolic AI as a pathway. This research shows a novel framework that improves explainability, precision and compliance with the policy enforcement by improving the status with the respect of both neural perception and symbolic logic. The future work includes a broader deployment, adversarial resilience with the Zero Trust models.

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