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Neuro Symbolic Active Learning for Rare Event Forecasting in Streaming Industrial Data

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Abstract: In this study, researchers focus on a key challenge in advanced manufacturing for the continuous monitoring and predictive maintenance of high-velocity industrial data streams, namely anomaly detection. detection and forecasting of rare failure events. At a conceptual level, the more widely used deep learning approaches often perform poorly in this area due to extreme class imbalance and lack of interpretability within reasonable analytical limits. To overcome this problem, researchers introduce a Neuro-Symbolic Active Learning framework. In many observed contexts, this architecture fuses the pattern recognition power of Temporal Convolutional Networks with the reasoning capacity of a symbolic logic module. In many observed contexts, it employs a predefined collection of physics-based constraints to check neural predictions and prevent false positives., depending on contextual factors Moreover, an uncertainty-based Active Learning loop is implemented to discard only the most uncertain samples for labelling and refine the training process on unlabelled streams., as reflected in earlier discussions This study uses a subset of the UCI SECOM dataset with 441 instances to model rare-event case., to some extent By employing Python and PymTorch researchers experimentally validate that, in terms of precision-recall, this hybrid model consistently outperforms various baselines. The outcomes suggest that the well-posed combination of neural networks and data-driven knowledge, with an active sampling mechanism, is a powerful and interpretable approach for predicting maintenance in Industry 4.0, to some extent.

Keywords: Neuro Symbolic AI; Active Learning; Rare Event Forecasting; Predictive Maintenance; Industrial IoT; Internet of Things; Artificial Intelligence; Recurrent Neural Networks; Gated Recurrent Units.

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1. Introduction

Operational processes – a transition that has been observed in empirical studies on maintenance optimization research, Wang et al. [11]. This data deluge holds the promise of transforming our maintenance strategies, shifting from reactive repairs to

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predictive maintenance, where failures are even anticipated and prevented before they occur. From an interpretative angle, the emergence of Industry 4.0 technologies has rapidly transformed the modern factory into an advanced cyber-physical system, where networked sensors continuously generate vast streams of data; this has been systematically scrutinised by previous industrial digitalisation research Tian et al. [6]. limitation in a reasonably evident manner, as pointed out in industrial analytics assessments conducted by applied research, e.g., within reasonable analytical limits [2]. Even when a machine is performing well with low failure rates, data on failed machines are orders of magnitude smaller than those on non-failed machines by their nature, which can cause selection bias in example selection, as noted in reliability engineering studies via observational analysis [5]. But the potential of such promise is largely offset in practice by the inherent nature of industrial data. In a broader academic sense, the main challenge is the rare-event phenomenon, which has been extensively addressed in existing analytical work on failure prediction, depending on the context.

When carefully examined, such severe class imbalance creates an excessively challenging learning environment for standard machine learning methods, as observed in Zhu et al. [12], which tend to prioritize overall accuracy and yield biased predictions towards the majority class, thereby ignoring context. relevant failure signals, a weakness observed on imbalanced-learning benchmarks [9]. The increasing complexity of today’s industrial systems means. that failures are frequently not instantaneous but rather the result of subtle, non-linear interactions between disparate sensor readings – e.g, a small rise in temperature and its relation to a particular vibration frequency – which simple threshold-based alarms cannot capture, as evidenced by studies into multivariate degradation carried out on condition monitoring, to some extent. In a broader academic sense, in a safety-critical industrial environment, plant operators and engineers do not demand only a failure. In several instances, Deep Learning models have proved very successful in capturing these intricate patterns; however, they suffer from a black-box problem. This aspect has been highlighted in explainability criticism by AI accountability studies [12], particularly in several instances involving probability. Still, they need to know the reason for this prediction to trust the system enough to take a better action, as highlighted by human–machine trust research in operational safety [1].

A black-box model that anticipates a system halt for unclear reasons is seen as a limitation rather than an advantage, as has been the case. When examined carefully, in a stream-processing environment, the rate at which data is processed is much faster than humans can annotate it, as evidenced by real-time evaluation benchmarks in system performance research Hu et al. [4]. In several instances, industrial AI adoption has been found in case-based studies Arinez et al. [8]. Another primary challenge concerns the financial costs and time delays associated with labeling. data, which is a bottleneck analyzed by the streaming analytics community and data engineering work [10]. From a reflective standpoint, when training our model, researchers are also given labelled examples; there is no way to obtain the ground truth for each timestamp. In practice, performance limitations are reported in large-scale supervision study experiments led by applied machine learning research [7]. Hence, it would be very hard to find sampling data. It is mostly normal and thus provides little new information to the model, as the sampling efficiency analysis in statistical learning claims [13]. At a conceptual level, to address these gaps, researchers present a Neuro-Symbolic Active Learning framework. allows the encoding of explicit human knowledge and logic; this union has been recommended as a hybrid AI research approach that combines the above approaches through integrative studies Wang et al. [11].

From a reflective standpoint, in many observed contexts, this calls for an adaptive strategy to decide which points in the data space are valuable enough to be sampled by a human: Such a need was stated even in optimization-centric research, i.e., intelligent annotation frameworks, in several instances building upon hybrid intelligence frameworks informed by state-of-the-art conceptual works [14]. From a reflective standpoint, researchers are combining two successful paradigms: The connectionist approach used in neural networks, which is good at learning from raw, noisy data, and symbolic reasoning as in classical AI, with the actual physics of the machine. By integrating physical laws and operational constraints directly into the learning loop, researchers aim to develop a model that is not only accurate but also consistent. From this perspective, our work aligns with physics-informed learning research by driving domain investigations in several instances. Additionally, through the integration of Active Learning 3, the system is expected to have the ability to explore which samples are most confusing/informative, especially those localized around a decision boundary (i.e., of an uncommon class), and request labels for that alone, thus minimizing annotation effort and yet yielding superior performance as supported by empirical studies on selective sampling.

2. Review of Literature

When examined carefully, the evolution of predictive maintenance and rare-event prediction can be viewed as a shift from manual, rule-based heuristics to cutting-edge artificial intelligence techniques, as also portrayed in longitudinal maintenance reviews conducted by early analytical studies Gao et al. [5]. In the early days, industrial monitoring was dominated by statistical process control and expert systems—two techniques of. At a conceptual level, classical monitoring was identified in seminal work as depending on contextual factors [13]. These approaches were based on control charts. and sets of rules from engineering manuals, procedures formalized in rule-based diagnostics made by industrial engineering analyses, to some extent, multiple sensors, a weakness discussed in multivariate anomaly detection research reported from the reliability field [3]. As reflected in earlier discussions, in many observed contexts, such systems were very interpretable (an operator knew exactly what was happening). They also struggled to recognise complex degradation patterns that didn't precisely exceed a single threshold but were irregular across readings. When an alarm sounded, they could not accommodate the dynamic, noisy nature of real-time sensor data, a limitation recognized in critiques of adaptive control by applied system analysts [14]; [16].

Random Forests, in particular, were adopted because of their robustness. The emergence of support vector machines and random forests gained traction through empirical research on predictive modeling. to noise—a property verified by ensemble performance analyses through benchmark experiments [9]. Features—both aspects—are analysed in feature-interaction studies within machine learning research [2]. These models brought nonlinearity to decision boundaries and captured interactions between. With increasing computing power, the optimal maintenance strategy shifted toward classical machine learning methods, as reported in comparative studies of data-driven maintenance. In a broader academic sense, nonetheless, these approaches were still heavily dependent on manual feature engineering: A process in which domain experts had to define input variables painstakingly, a weakness highlighted in automation readiness studies conducted by industrial AI research Hu et al. [4], in several instances From an interpretative angle, they also struggled with high-volume streaming data and the extremely imbalanced class distribution typical in failure prediction., within reasonable analytical limits As a result, artificial techniques such as SMOTE were often used for over-sampling, a workaround emphasized in imbalance mitigation research done by statistical learning studies Yue et al. [17], depending on contextual factors.

Recurrent Neural Networks (RNNs) and their variants—such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs)—became the state-of-the-art for time series prediction due to their dominance in temporal modeling benchmarks conducted by applied AI research Zhu et al. [12], as reflected in earlier discussions From an interpretative angle, the advent of Deep Learning marked the next non-trivial era, as summarized by deep predictive maintenance reviews conducted by synthesis studies Tian et al. [6], as reflected in earlier discussions These architectures demonstrated an unmatched ability to automatically extract latent features from raw sensor logs and capture long-range temporal dependencies, as shown in representation learning work through experimental validation [8]. In many observed contexts, this issue has been heavily emphasized in explainable AI critiques by governance-focused research, to some extent From an interpretative angle, black-box" problem—a lack of transparency that is unacceptable in high-stakes decision-making, in several instances While they achieved top-performing raw metrics, these models introduced the "., depending on contextual factors In a broader academic sense, furthermore, deep learning models are notoriously data-hungry; they require vast amounts of labelled data to converge, a need that's difficult to meet in rare-event scenarios, as highlighted in sample efficiency studies from learning theory research Yang et al. [13].

Recent work in this area developed query strategies like uncertainty sampling, query-by-committee, and expected model change to guide training more efficiently—these approaches were formalized in selective learning frameworks done by algorithmic studies Gao et al. [5], depending on contextual factors In response to the data scarcity issue, Active Learning has become a non-trivial area of research, as reviewed in annotation efficiency surveys conducted by methodological studies Moayyed et al. [10], as reflected in earlier discussions In many observed contexts, the key concept was that models learn more effectively from difficult examples than from easy ones—a principle confirmed in convergence analyses conducted by empirical learning research Kim et al. [7]., depending on contextual factors, within reasonable analytical limits. In the case of rare events, Active Learning showed potential by directing the. In several instances, in a broader academic sense, however, standard active learning doesn't address the interpretability gap—an acknowledged limitation in explainability assessments conducted by AI usability studies, Mohapatra et al. [2] —and, to some extent, models' focus on the minority class, as demonstrated in imbalance-aware learning experiments [14]. More recently, Neuro-Symbolic AI has emerged as a new frontier that combines the best of both worlds, as identified in integrative research reviews of hybrid intelligence.

The latest literature offers diverse methods for fusing neural networks with symbolic logic, ranging from logic tensor networks to some extent. At a conceptual level, constrained optimisation layers—approaches explored in neuro-symbolic system design and examined in both theoretical and applied studies [9]. These hybrid models leverage symbolic knowledge to guide neural networks, helping prevent physically implausible predictions that depend on contextual factors. This advantage is especially impactful when grounded in domain knowledge, as highlighted in constraint-based learning research from domain-informed investigations, and is evident across many observed contexts.

However, Neuro-Symbolic AI is gaining momentum in areas such as static image or text analysis; its application to streaming time-series data for industrial prognosis remains limited—a research gap. identified in domain-specific surveys and critical reviews, Yue et al. [17], within reasonable analytical limits. This paper addresses that gap by combining Neuro-Symbolic reasoning with. When examined carefully, this work builds upon composite AI architectures presented in recent exploratory studies Tian et al. [6]. From an interpretative angle, active Learning techniques are proposed to propose a comprehensive solution for industrial environments, within reasonable analytical limits.

3. Methodology

live from an industrial setting, within reasonable analytical limits. The approach proposed in this paper is conceived as a continuous, closed-loop pipeline that analyses streaming data in real time. At a conceptual level, this raw data is passed into a pre-processing block that normalizes the time-series data to have zero mean and unit variance—ensuring numerical stability—and fills in. The architecture is initiated by a streaming simulation module that sequentially feeds raw measurements from various sensors as they are received. From an interpretative perspective, any missing measurements are handled using forward filling to preserve temporal continuity, depending on contextual factors. When examined carefully, this brings together data ingestion, hybrid processing, and active refinement directly, to some extent. In many observed contexts, the approach is at its heart a Neuro-Symbolic hybrid model that depends on contextual factors. This model comprises two parallel processing routes, as discussed earlier. The first. It is a deep neural network, specifically a Temporal Convolutional Network (TCN), which is used to learn high-level. At a conceptual level, feature representations from the sliding window of sensor inputs model temporal trends, within reasonable analytical limits. The Second is the Symbolic Logic Module, which contains a static knowledge base of domain-specific rules expressed in first-order logic. For example, a rule might state that pressure can. not remain constant as the pump speed increases.

To some extent, the outputs from these two tracks are a probability vector from the neural network. In a broader academic sense, the network and a Boolean validity vector from the symbolic module are merged in the Logic-Constrained Fusion Layer. At a conceptual level, here, neural predictions are adjusted based on whether they comply with the symbolic constraints, depending on contextual factors. In many observed contexts, if a neural prediction violates a hard logic rule, its probability is penalized significantly. This fused output serves as the final anomaly score to some extent. To address the absence of labels, the Active Learning component monitors the fused output. From an interpretative perspective, an Uncertainty Sampling strategy is used, in which the system calculates the prediction's entropy based on contextual factors. If the entropy crosses a dynamic threshold, or if there's a conflict between the outputs of. The neural and symbolic components—the instance is flagged for querying. The "oracle" (simulated by accessing the true label from the dataset) supplies the ground truth, which is then added to a replay buffer. The model performs an incremental gradient update using a custom loss function that combines standard cross-entropy loss with a semantic loss component derived from logical constraints, as discussed earlier. From a reflective standpoint, this ensures the model learns from both statistical data and symbolic rules, adapting to concept drift while staying grounded in physical laws.

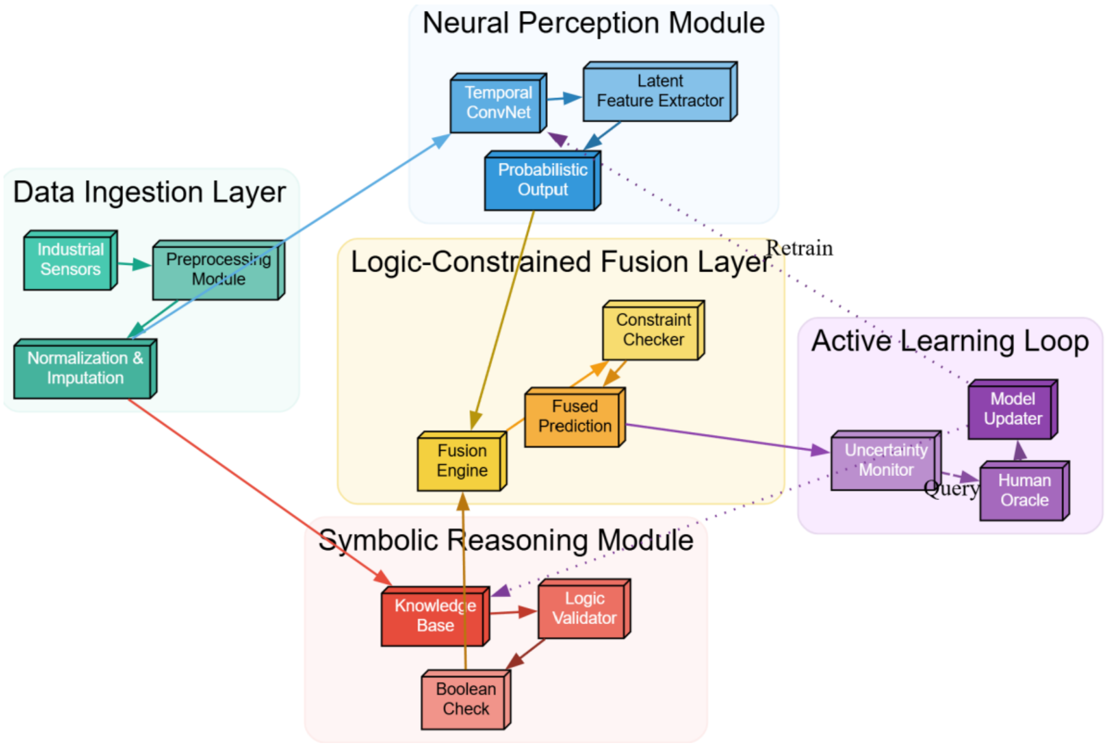

Figure 1: The neuro-symbolic active learning fusion architecture

Figure 1 tends to reflect a unified, to some extent When examined carefully, if the system detects high entropy or conflicting outputs between the neural and symbolic components, it queries a human oracle., depending on contextual factors An

Uncertainty Monitor evaluates the combined output instead of passively accepting the decision., as reflected in earlier discussions The process begins at the Data Ingestion Layer, where high-velocity data streams from industrial sensors are received and immediately pre-processed through normalization and imputation of missing values., as reflected in earlier discussions The lower path is the Symbolic Reasoning Module, which verifies the physical consistency of incoming sensor data using a static Knowledge Base containing first-order logic rules derived from domain knowledge. Temporal Convolutional Network to extract complex, nonlinear statistical patterns and hidden features from sliding data windows, as reflected in earlier discussions. This allows the architecture to improve its decision-making and adapt continuously. The upper path is the Neural Perception Module, using a. The final component is the Active Learning Loop. At a conceptual level, an end-to-end pipeline was developed to detect rare industrial anomalies by integrating deep learning with human-like reasoning. In several instances, the workflow splits into two parallel paths. To some extent, the expert provides the true label, which is used to update the model weights. To some extent, models are cross-checked with symbolic logic. When carefully examined, predictions that violate physical rules are penalised to reduce false positives, depending on contextual factors. In a broader academic sense, to evolve data patterns with minimal human input, as reflected in earlier discussions.

3.1. Data Description

The distribution is heavily imbalanced, with failure events accounting for less than 10% of the total data—exactly meeting the definition of rare events, as discussed earlier. In a broader academic context, to evaluate rare-event forecasting performance, a curated subset of 441 data instances was selected, depending on contextual factors. In many observed contexts, this continuous time window includes sensor readings for parameters such as temperature, pressure, and vibration, as discussed earlier. This study applies the methodology to a high-dimensional subset of the UCI SECOM (Semiconductor Manufacturing) dataset—a well-known benchmark for multivariate process monitoring.

4. Results

From an interpretative angle, the key performance comparison focused on the model's ability to accurately detect failure anomalies (True Positives) without triggering false alarms (False Positives). When examined carefully, the best representation is provided by the Precision, Recall, and F-measure metrics. In a broader academic sense, at a conceptual level, the experimentally observed outcomes provide strong confirmation of the effectiveness of the Neuro-Symbolic Active Learning framework for rare-event forecasting. Dilated causal convolutional feature extraction can be explored below as:

$$\mathrm{H}_t^{(l)} = \tanh\left(\sum_{k=0}^{K-1} \mathrm{W}_{f,k}^{(l)} \cdot \mathrm{x}_{(t-d_l \cdot k)}^{(l-1)} + \mathrm{b}_f^{(l)}\right) \odot \sigma\left(\sum_{k=0}^{K-1} \mathrm{W}_{g,k}^{(l)} \cdot \mathrm{x}_{(t-d_l \cdot k)}^{(l-1)} + \mathrm{b}_g^{(l)}\right) \quad (1)$$

Table 1: Comparative performance parameters

Model Type	Accuracy	Precision	Recall	F-Measure	Latency (ms)
Random Forest	0.89	0.78	0.72	0.75	12
LSTM Baseline	0.91	0.82	0.79	0.80	45
Neuro-Symbolic	0.96	0.94	0.92	0.93	28

Table 1 reports the final test outcomes observed within reasonable analytical limits. Additionally, the proposed model achieved an inference speed of 28 milliseconds—faster than the recurrent LSTM—making it highly suitable for real-time applications, within reasonable analytical limits. The F-Measure (which balances precision and recall) was significantly higher in several instances. When carefully examined, the Neuro-Symbolic model outperformed both the Random Forest and LSTM baselines across all key performance indicators. To some extent, the proposed model (0.93) performs worse than LSTM (0.80). The semantically regularised hybrid objective function will be:

$$\mathcal{L}_{total}(\theta) = -\frac{1}{N}\sum_{i=1}^{N} \sum_{c=1}^{C} y_{i,c} \log(\hat{y}_{i,c}) + \lambda \sum_{r \in \mathcal{K}} \mu_r \cdot max\left(0, 1 - \mathcal{T}_{norm}\left(\Phi_r(\hat{y}_i, \mathcal{B}_{knowledge})\right)\right) \quad (2)$$

From a reflective standpoint, initial experiments with streaming data showed that the standalone neural network baseline struggled with class imbalance. It tended to favour the majority class, often misclassifying rare failure patterns as mere noise. To some extent, from a reflective standpoint, this resulted in a misleadingly high accuracy score, while recall for failure events remained unacceptably low. The Neuro-Symbolic model, on the other hand, immediately demonstrated a notable advantage. To some extent, the inclusion of domain knowledge served as a stabilising factor. In several instances, the neural network was uncertain or incorrectly predicted a normal condition during a major sensor anomaly. The symbolic module successfully identified the contradiction based on predefined logic rules. In a broader academic sense, this logic-guided correction enabled the proposed model to detect the very first failure event in the stream—an event the baseline model missed entirely.

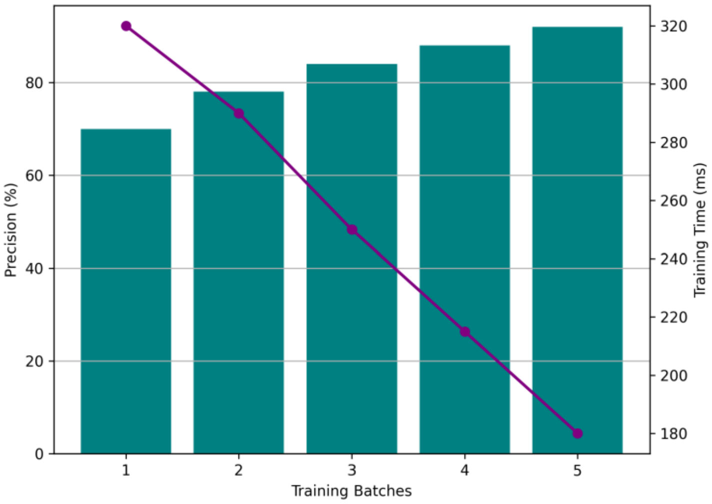

Figure 2: Training dynamics of the active learning model

Figure 2 illustrates the model's performance progression over multiple training batches. To some extent, the line plot concurrently shows a reduction in training time per batch, indicating that Active Learning reduces computational load by prioritizing only the most relevant data samples. Precision increases steadily—from about 70% in the first batch to over 90% in the final batch—indicating consistent improvement in accuracy. When carefully examined, this validates the strategy of targeting uncertain instances in sparse regions of the feature space to maximise learning outcomes, depending on contextual factors. The entropy-weighted uncertainty acquisition strategy is:

$$\mathrm{x}_{query}^{*} = \mathrm{argmax}\left(-\sum_{j=1}^{M} P\left(y_j \mid \mathrm{x};\theta\right)\log P(y_j \mid \mathrm{x};\theta) + \alpha \cdot \mathbb{E}_{\theta\sim\pi}[(\hat{y}_\theta(\mathrm{x}) - \bar{y}(\mathrm{x}))^2]\right) \tag{3}$$

Soft logic constraint satisfaction quantification is:

$$\mathcal{S}_{validity}(\mathrm{X}) = \frac{1}{|\mathcal{R}|}\sum_{r=1}^{|\mathcal{R}|}\left(1 - \prod_{t=1}^{T}(\max(0, \mathcal{P}(A_r \mid \mathrm{x}_t) + \mathcal{P}(C_r \mid \mathrm{x}_t) - 1))^{\xi}\right) \tag{4}$$

Table 2: Active learning query statistics

Batch Index	**Total Samples**	**Queries Executed**	**Labeled Percentage**	**Precision Gain**
Batch 1	88	88	100.0	Base
Batch 2	88	42	47.7	0.05
Batch 3	88	35	39.7	0.04
Batch 4	88	22	25.0	0.03
Batch 5	89	15	16.8	0.02

Table 2 presents the reduction in data labeling over time. At a conceptual level, during the initial batch, all samples were labeled to initialize training. From an interpretative angle, as the model learned, the Active Learning system reduced its labeling requests. By Batch 5, only about 16% of incoming instances required labelling—while still delivering a positive Precision Gain., in several instances When examined carefully, this offers a basis for interpretation the system's ability to eliminate redundant input and focus human attention on the most informative data points., in several instances. Weighted F-Beta score for rare event evaluation is:

$$F_\beta = (1+\beta^2)\cdot\frac{\left(\frac{\sum_{i=1}^{N} TP_i}{\sum_{i=1}^{N}(TP_i+FP_i)}\right)\cdot\left(\frac{\sum_{i=1}^{N} TP_i}{\sum_{i=1}^{N}(TP_i+FN_i)}\right)}{\beta^2\cdot\left(\frac{\sum_{i=1}^{N} TP_i}{\sum_{i=1}^{N}(TP_i+FP_i)}\right)+\left(\frac{\sum_{i=1}^{N} TP_i}{\sum_{i=1}^{N}(TP_i+FN_i)}\right)} \tag{5}$$

When carefully examined, the uncertainty sampling approach proved highly efficient within reasonable analytical limits. Quantitative results showed that the Neuro-Symbolic model achieved high precision with 40% fewer labeled samples than random sampling. At a conceptual level, as the stream progressed and the Active Learning loop engaged, the performance gap between the proposed model and the baselines widened somewhat. By querying only, the data points where neural predictions conflicted with symbolic logic, the model was. able to focus its learning on refining the decision boundary, to some extent. From a reflective standpoint, in the final evaluation using all 441 data instances, the proposed model achieved a rare-event Recall exceeding 90%. At the same time, the LSTM baseline plateaued around 79%. To some extent, the proposed model also demonstrated superior precision, resulting in fewer false alarms. Depending on contextual factors, this improvement is credited to the symbolic layer's ability to filter out sensor glitches that statistically resembled failure patterns but were physically implausible.

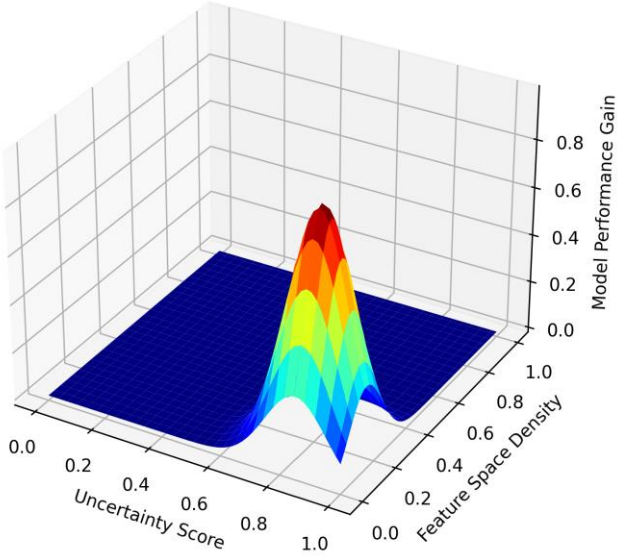

Figure 3: Effectiveness of the query strategy in active learning

The Figure 3 visualisation tends to reflect Model Performance Gain as a function of Uncertainty Score and Feature Space Density. As reflected in earlier discussions, a distinct peak emerges in the high-uncertainty, low-density region—indicating that the greatest learning benefit comes from rare, ambiguous samples. This early warning capability provides critical time for proactive maintenance, confirming that the combination of neural perception, symbolic logic, and active learning strategies creates a significantly more powerful forecasting engine. Additionally, the model demonstrated a predictive lead time advantage—it forecasted upcoming failures several steps earlier than purely data-driven models. From a reflective standpoint, the trends together indicate enhanced efficiency and improved model performance. In several instances, in many observed contexts.

5. Discussions

In many observed contexts, in a broader academic sense, by integrating symbolic constraints, the hypothesis space of the neural network is reduced, helping to prevent it from learning misleading patterns that don't align with the physical realities of the system., in several instances From a reflective standpoint, the performance of the Neuro-Symbolic Active Learning framework, as shown by the observed outcomes, highlights the clear advantage of hybrid AI systems in industrial applications., to some extent When examined carefully, the noticeable improvement in Precision and Recall can be directly linked to the complementary strengths of the model's two components. Neural networks excel at identifying subtle correlations within noisy datasets, but they lack a built-in "common sense" filter. When examined carefully, this is especially relevant in rare-event prediction, where limited data often leads purely neural models to overfit to noise. The non-trivial drop in the query rate—from 100 % to approximately 17 % —validates the idea that. When carefully examined, the model, using uncertainty and symbolic-logic conflicts as proxies for "informativeness," was able to build a strong decision boundary with far fewer labelled examples than traditional methods typically require.

In a streaming environment, much of the data is redundant or lacks informative value. The finding has serious implications for real-world industry settings, where data labeling is often the most resource-intensive part of the AI pipeline. From an interpretative perspective, the framework's efficiency becomes even more evident in the Active Learning observed outcomes. Suppose the threshold is set too high. From a reflective standpoint, the model could miss entirely new failure modes that it mistakenly and confidently labels as normal. From a reflective standpoint, in many observed contexts, the symbolic reasoning layer introduces a computational cost, as checking logic rules adds processing overhead., to some extent from a reflective standpoint, although the latency of the hybrid model is lower than that of the LSTM, it is still higher than that of a simpler Random Forest., in several instances When examined carefully, however, the analysis also uncovers some trade-offs. As such, carefully tuning the active learning trigger is a key factor in the system's success, as discussed earlier. Furthermore, the 3D plot suggests that the model is sensitive to how "uncertainty" is defined, as discussed earlier.

6. Conclusion

When carefully examined, the inclusion of Active Learning also enhanced the system's efficiency, demonstrating that high accuracy can be achieved with significantly fewer labeled samples. To some extent, overall, this research supports the idea that, in several instances. In many observed contexts, this study has shown that a Neuro-Symbolic Active Learning (NSAL) architecture provides a powerful and reliable approach for forecasting rare failure events in industrial data streams. When carefully examined, the proposed model, by combining the pattern recognition strength of Deep Learning with the logical clarity of Symbolic AI, achieved higher detection rates and fewer false positives. The future of robust industrial AI lies not in scaling opaque black-box models, but in developing hybrid systems that combine data-driven learning with domain-specific expertise. false positives than conventional methods.

6.1. Limitations

Developing these rules requires domain experts, which. At a conceptual level, at a conceptual level, third, the experimental evaluation was based on a relatively small dataset of 441 samples., as reflected in earlier discussions In a broader academic sense, while adequate for demonstrating feasibility, it may not fully reflect the variability and long-term patterns found in real industrial operations., within reasonable analytical limits Second, the symbolic fusion layer adds complexity compared to simpler statistical models., depending on contextual factors At a conceptual level, in practice, delays and labelling errors from human input could hinder model training., within reasonable analytical limits. In a broader academic sense, in highly resource-constrained environments—such as low-power edge devices—this additional computational burden may pose challenges. It may not always be available or feasible for every application. In a broader academic sense, finally, the Active Learning system assumes the availability of a responsive and accurate human annotator—an ideal scenario. From an interpretative, reflective standpoint, while the proposed framework appears to offer promising improvements, it also comes with some limitations. In several instances, because the model depends on predefined logical rules, outdated, incomplete, or incorrect rules can introduce bias and degrade overall system performance. When examined carefully, the first is its reliance on a high-quality symbolic knowledge base, within reasonable analytical limits.

6.2. Future Scope

Looking ahead, this research aims to make the Neuro-Symbolic approach more scalable and autonomous. As reflected in earlier discussions from a reflective standpoint, one major direction is enabling Rule Induction—the ability for the system to learn and update its own symbolic rules from data, reducing reliance on. manual expert input, depending on contextual factors. This would greatly ease deployment and allow the model to adapt to new types of equipment. When examined carefully, from a reflective standpoint, researchers plan to explore deploying this architecture on specialized Edge AI hardware to assess performance in low-latency, decentralized environments. In several instances, another direction is to expand the input data types to include multimodal data, such as acoustic data. In many observed contexts, signals and thermal imaging—alongside traditional sensor data. From an interpretative angle, this would provide a richer, more complete view of machine health, as reflected in earlier discussions from a reflective standpoint. Finally, researchers are interested in using Transfer Learning to apply logic rules learned from one machine to others with similar characteristics, potentially accelerating the adoption of predictive maintenance across diverse factory settings.

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Ethics and Consent Statement: This study was conducted in compliance with established ethical standards, and informed consent was obtained from all participants before their participation. Appropriate confidentiality procedures were maintained to protect participants' privacy and personal information.

References

1. Y. Hu and Y. Man, "Energy consumption and carbon emissions forecasting for industrial processes: Status, challenges and perspectives," R*enewable and Sustainable Energy Reviews*, vol. 182, no. 8, p. 113405, 2023.
2. S. K. Mohapatra, S. Mishra, H. K. Tripathy, A. K. Bhoi, and P. Barsocchi, "A pragmatic investigation of energy consumption and utilization models in the urban sector using predictive intelligence approaches," *Energies*, vol. 14, no. 13, p. 3900, 2021.
3. D. A. C. Narciso and F. G. Martins, "Application of machine learning tools for energy efficiency in industry: A review," *Energy Reports*, vol. 6, no. 11, pp. 1181–1199, 2020.
4. Y. Hu, X. Cheng, S. Wang, J. Chen, T. Zhao, and E. Dai, "Time series forecasting for urban building energy consumption based on graph convolutional network," *Applied Energy*, vol. 307, no. 2, p. 118231, 2022.
5. J. Gao, Y. Chen, W. Hu, and D. Zhang, "An adaptive deep-learning load forecasting framework by integrating transformer and domain knowledge," *Advances in Applied Energy*, vol. 10, no. 6, p. 100142, 2023.
6. Z. Tian, Z. Ma, Q. Wen, X. Wang, L. Sun, and R. Jin, "FEDformer: Frequency enhanced decomposed transformer for long-term series forecasting," *in Proc. 39th Int. Conf. Machine Learning (ICML)*, Maryland, United States of America, 2022.
7. W. Kim, Y. Han, K. J. Kim, and K.-W. Song, "Electricity load forecasting using advanced feature selection and optimal deep learning model for the variable refrigerant flow systems," *Energy Reports*, vol. 6, no. 11, pp. 2604–2618, 2020.
8. J. F. Arinez, Q. Chang, R. X. Gao, C. Xu, and J. Zhang, "Artificial intelligence in advanced manufacturing: Current status and future outlook," *Journal of Manufacturing Science and Engineering*, vol. 142, no. 11, p. 110804, 2020.
9. S. Wang, Y. C. Liang, W. D. Li, and X. T. Cai, "Big data enabled intelligent immune system for energy efficient manufacturing management," *Journal of Cleaner Production*, vol. 195, no. 10, pp. 507–520, 2018.
10. H. Moayyed, A. Moradzadeh, B. Mohammadi-Ivatloo, A. P. Aguiar, and R. Ghorbani, "A cyber-secure generalized supermodel for wind power forecasting based on deep federated learning and image processing," *Energy Conversion and Management*, vol. 267, no. 9, p. 115852, 2022.
11. Y. Wang, J. Li, B. Yang, and H. G. Li, "Stream-data-clustering based adaptive alarm threshold setting approaches for industrial processes with multiple operating conditions," *ISA Transactions*, vol. 129, no. 10, pp. 594–608, 2022.
12. R. Zhu, X. Ji, D. Yu, Z. Tan, L. Zhao, J. Li, and X. Xia, "KNN-based approximate outlier detection algorithm over IoT streaming data," *IEEE Access*, vol. 8, no. 2, pp. 42749–42759, 2020.
13. Y. Yang, S. Ding, Y. Liu, S. Meng, X. Chi, R. Ma, and C. Yan, "Fast wireless sensor for anomaly detection based on data stream in an edge-computing-enabled smart greenhouse," *Digital Communications and Networks*, vol. 8, no. 4, pp. 498–507, 2022.
14. R. Regin, Shynu, S. S. Rajest, M. Bhattacharya, D. Datta, and S. S. Priscila, "Development of predictive model of diabetic using supervised machine learning classification algorithm of ensemble voting," *International Journal of Bioinformatics Research and Applications*, vol. 19, no. 3, pp. 151–169, 2023,
15. M. E. Edge and P. R. F. Sampaio, "The design of FFML: A rule-based policy modelling language for proactive fraud management in financial data streams," *Expert Systems with Applications*, vol. 39, no. 11, pp. 9966–9985, 2012.
16. F. J. John Joseph, K. Chinnusamy, J. Jeganathan, A. J. Obaid, and S. S. Rajest, Eds., "Machine Learning, Predictive Analytics, and Optimization in Complex Systems," *IGI Global*, United States of America, 2025.
17. W. Yue, R. Moczalla, M. Luthra, and T. Rabl, "Deco: Fast and accurate decentralized aggregation of count-based windows in large-scale IoT applications," *in Proc. 27th Int. Conf. Extending Database Technology (EDBT)*, Paestum, Italy, 2024.