

Tribo-AI: a Neuro-Symbolic Geometric Reasoning for Scratch Measurement in Tribological SEM Images

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Abstract

Scanning electron microscopy (SEM) images are widely used in tribological analysis to inspect wear mechanisms and surface scratches. However, the interpretation of scratch structures and the estimation of geometric measurements from SEM images remain challenging due to visual uncertainty, heterogeneous surface patterns, and the need for expert geometric reasoning. This paper presents *Tribo-AI*, a neuro-symbolic framework for interpretable scratch analysis and width estimation from SEM images. The framework combines Mask R-CNN-based perception with symbolic geometric abstraction and Possibilistic Answer Set Programming (ASP) reasoning. Neural detections are transformed into symbolic geometric relations representing ridge structures, spatial configurations, and candidate scratch boundaries. Possibilistic ASP rules are then used to generate and rank plausible width hypotheses under uncertainty. Unlike purely neural approaches, the proposed framework does not directly regress scratch measurements from images. Instead, measurements emerge from symbolic geometric reasoning over uncertain visual detections, enabling explicit reasoning traces and interpretable measurement generation. The current prototype additionally supports human-in-the-loop interaction through expert feedback and confidence adjustment. The proposed framework illustrates how possibilistic symbolic reasoning can complement neural perception for uncertainty-aware tribological inspection and geometric interpretation.

Keywords

Neuro-symbolic AI, Possibility Theory, Answer Set Programming, Tribology, SEM Image Analysis, Scratch Measurement, Geometric Reasoning, Explainable AI

1. Introduction

Tribological surface analysis frequently relies on *scanning electron microscopy* (SEM) images to characterize wear mechanisms, *scratch* morphology, and material degradation processes [1, 2]. However, SEM-based scratch interpretation remains challenging due to the high variability of surface structures, the presence of debris and artifacts, and the need for expert-driven geometric interpretation [3]. Recent discussions [4, 1] have additionally highlighted the limited availability of annotated SEM datasets and the difficulty of constructing reproducible computational pipelines for tribological image analysis.

Machine learning approaches have recently been explored in tribology for tasks such as wear classification, surface characterization, and feature detection from microscopy images [2]. In particular,

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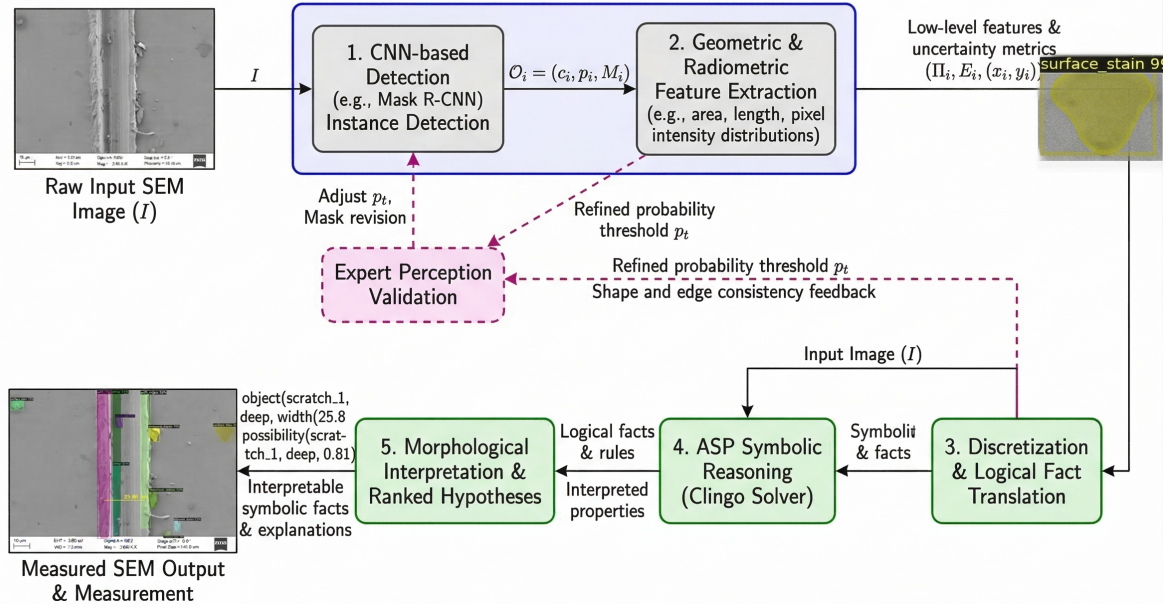


Figure 1: Tribo-AI neuro-symbolic pipeline. The system extracts low-level tribological features (Possibility Π_i /Energy E_i) from SEM images using a Deep Convolutional Neural Network (CNN). Experts provide shape-based feedback to refine the CNN model, which handles high variance and noisy data effectively. These features are discretized into possibilistic Answer Set Programming (ASP) facts. The symbolic module (flowing right-to-left) uses a Clingo solver [8] to perform structural reasoning. The final output provides a verified measured SEM image and a complete set of validated symbolic facts.

convolutional architectures and instance segmentation methods have shown promising results for detecting tribological structures from SEM images. Nevertheless, these approaches primarily operate at the level of visual pattern recognition and confidence estimation. High-level geometric measurements derived from expert tribological reasoning, such as scratch width estimation from ridge structures (Figure 2), are not directly represented by standard neural predictors.

Knowledge representation and reasoning (KR) mechanisms provide a complementary framework for explicit geometric interpretation and uncertainty-aware reasoning. In particular, *possibility theory* [5] offers a well-established formalism for representing graded uncertainty, whereas *Answer Set Programming* (ASP) provides a declarative framework for non-monotonic reasoning and symbolic inference [6]. Recent neuro-symbolic research has investigated the integration of neural perception with symbolic reasoning to improve interpretability and structured inference [7].

Contributions. This paper presents *Tribo-AI*, a neuro-symbolic framework for SEM scratch interpretation integrating convolutional perception, symbolic geometric abstraction, and possibilistic ASP reasoning. The framework combines Mask R-CNN-based detection of tribological structures with symbolic geometric relations to infer plausible scratch boundaries and generate ranked width measurements under uncertainty. Importantly, the proposed measurements are not directly regressed by the neural model, but emerge from symbolic reasoning over uncertain visual detections. The main contributions of this work are: 1) a neuro-symbolic pipeline for SEM scratch interpretation, 2) a symbolic geometric abstraction layer transforming neural detections into geometric predicates, 3) a possibilistic ASP reasoning mechanism for uncertainty-aware scratch width estimation, and 4) an interactive human-in-the-loop framework supporting expert validation and feedback. An online version of Tribo AI can be found in: <https://tribo.project.cs.umu.se/>

Running example. Figure 2 illustrates the running example used throughout the paper. The left image shows the original SEM scratch image provided as input to Tribo-AI, whereas the right image presents the symbolic geometric interpretation generated by the neuro-symbolic pipeline. The perception stage

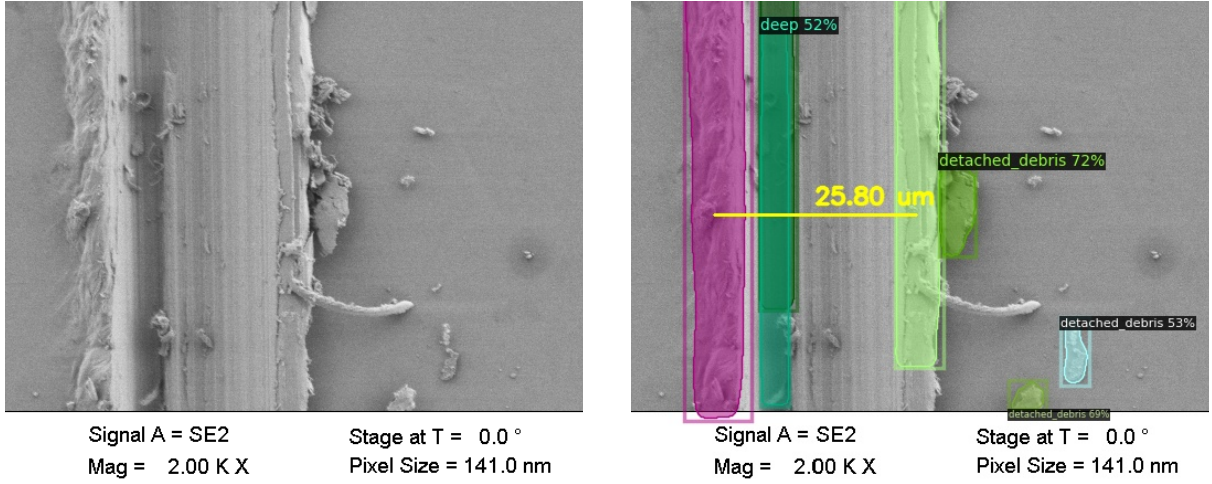


Figure 2: Running example used throughout the paper. Left: original SEM scratch image. Right: symbolic geometric interpretation generated by Tribo-AI, including detected tribological structures and inferred scratch width measurement obtained through possibilistic ASP reasoning.

detects tribological structures such as `with_ridges`, `deep`, `detached_debris`, and `surface_stain`, together with confidence values produced by the neural detector. These detections are transformed into symbolic geometric relations and interpreted through possibilistic ASP rules to infer plausible ridge boundaries and estimate scratch width.

In this example, the symbolic reasoning stage infers a dominant ridge pair and derives a width estimate of $25.80 \mu m$. Importantly, the measurement is not directly regressed by the neural model itself, but emerges from symbolic geometric reasoning over uncertain visual detections.

2. Neuro-symbolic scratch interpretation

Tribo-AI combines convolutional visual perception with symbolic possibilistic reasoning to derive interpretable geometric measurements from SEM images of surface scratches. The framework is based on the assumption that local visual detections alone are insufficient for reliable tribological interpretation, since width estimation depends on geometric relations between multiple uncertain structures, including ridges, groove boundaries, debris regions, and symmetry patterns.

Possibilities as energy-based neural values. The uncertainty values used by the symbolic reasoning layer are derived directly from the neural energy landscape produced by the perception module. Following the energy-based learning framework of LeCun et al. [9], the CNN assigns a scalar energy value to each candidate tribological structure, where lower energies correspond to more compatible visual configurations.

Let $z(id, c)$ denote the neural activation (logit) associated with class c (e.g., `deep`, `detached`, etc.) for a detected region id . Following the energy-based interpretation, we define an energy function

$$E(id, c) = -z(id, c), \quad (1)$$

such that highly activated detections correspond to lower energy states. To integrate these neural values into the possibilistic reasoning framework, the energies are transformed into possibilistic certainty degrees through a decreasing mapping $\phi : \mathbb{R} \rightarrow [0, 1]$, following a recently proposed possibilistic interpretation of energy-based neural activations [10], satisfying:

$$E_1 \leq E_2 \Rightarrow \phi(E_1) \geq \phi(E_2).$$

In the current framework, the certainty degree associated with a detection is therefore computed as: $\Pi(id, c) = \phi(E(id, c))$. This transformation establishes an order-preserving correspondence between

neural compatibility and possibilistic plausibility: visually compatible structures with lower neural energy are assigned higher possibility values. The symbolic layer does not introduce an independent uncertainty mechanism disconnected from the neural network. Instead, the possibilistic reasoning process operates directly on uncertainty values induced by the neural energy landscape itself.

Symbolic geometric abstraction. The neural perception stage produces a finite set of visual detections extracted from an SEM image I . Let $\mathcal{D}(I) = \{d_1, \dots, d_n\}$ denote the set of detected tribological structures generated by the CNN-based perception module.

Definition 1 (Detected tribological structure). A detected tribological structure is a tuple $d = (id, c, E, x, y)$, where: 1) id is a unique symbolic identifier, 2) $c \in \mathcal{C}$ is a tribological class label, 3) $E \in [0, 1]$ is the possibilistic certainty associated with the detection, 4) $(x, y) \in \mathbb{R}^2$ denotes the geometric center of the detected structure.

The set $\mathcal{C}$ contains tribological categories from [4] such as:

$$\mathcal{C} = \{\text{with_ridges}, \text{deep}, \text{detached_debris}, \text{surface_stain}\}.$$

The symbolic abstraction layer transforms neural detections into symbolic geometric facts represented as: $\text{object}(id, c, E, x, y)$. For example, a ridge-like structure detected with high certainty may be represented as:

$$\text{object}(r_1, \text{with_ridges}, 0.91, 125, 84).$$

The geometric abstraction layer additionally derives symbolic spatial relations between detected structures.

Definition 2 (Possibilistic geometric distance predicate). Let $A = (id_A, c_A, E_A, x_A, y_A)$ and $B = (id_B, c_B, E_B, x_B, y_B)$ be two detected tribological structures. The possibilistic horizontal distance relation $h_dist(A, B, D, E)$ holds iff: $D = |x_A - x_B|$ and $E = \min(E_A, E_B)$. Similarly, the possibilistic vertical distance relation $v_dist(A, B, D, E)$ holds iff: $D = |y_A - y_B|$ and $E = \min(E_A, E_B)$.

The propagated certainty degree E represents the joint plausibility associated with the geometric relation between the two detected structures. The use of the minimum operator corresponds to the standard conjunction operator in possibility theory [5]. We extend the notion of a possibility logic program atom from [11].

Definition 3 (Possibilistic geometric atom). A possibilistic geometric atom is an expression of the form $\text{possibility}(id, c, x, y, p)$, where: 1) (id, c, x, y) identifies a symbolic tribological structure; and 2) $p \in [0, 1]$ is a possibility degree representing the plausibility of the detected structure.

The possibilistic degree is computed from the neural energy through a decreasing transformation function: $\phi : \mathbb{R} \rightarrow [0, 1]$, such that lower energy values correspond to higher possibility values. Thus, for a detection $d = (id, c, E, x, y)$, the associated possibility degree is: $p = \phi(E)$. For example, a ridge-like structure detected at position (x, y) with high plausibility may be represented as:

$$\text{possibility}(r_1, \text{with_ridges}, 125, 84, 0.91).$$

Possibilistic ASP reasoning. The symbolic geometric abstraction is interpreted through a possibilistic Answer Set Programming (ASP) framework to infer plausible scratch structures and corresponding width hypotheses under uncertainty.

Definition 4 (Possibilistic rule). A possibilistic rule is an expression of the form $\lambda : H \leftarrow B_1, \dots, B_m, \text{not } C_1, \dots, \text{not } C_n$, where: 1) H is the head atom, 2) $B_1, \dots, B_m$ are positive body literals, 3) $\text{not } C_1, \dots, \text{not } C_n$ are negation-as-failure literals, and 4) $\lambda \in [0, 1]$ is a possibility degree associated with the rule.

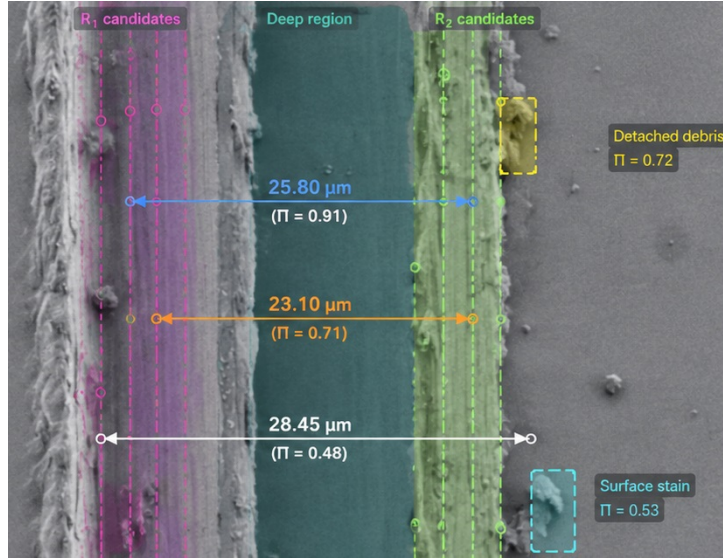


Figure 3: Competing scratch-width hypotheses inferred by the possibilistic geometric reasoning framework. Multiple candidate ridge boundaries generate alternative width measurements associated with different possibility degrees. The dominant hypothesis corresponds to a width estimate of $25.80 \mu\text{m}$ with the highest possibility value, while lower-ranked alternatives remain explicitly represented instead of being discarded through deterministic selection.

The reasoning process propagates possibility degrees through geometric relations using possibilistic aggregation principles inspired by possibilistic logic [5]. For example, ridge candidates are first inferred from sufficiently plausible ridge detections:

$$\text{ridge}(ID, P) \leftarrow \text{possibility}(ID, \text{with_ridges}, X, Y, P), P \geq \theta.$$

where θ denotes a minimum plausibility threshold. Pairs of approximately parallel ridges are then inferred geometrically:

$$\text{parallel_ridges}(R_1, R_2, P) \leftarrow \text{ridge}(R_1, P_1), \text{ridge}(R_2, P_2), v_dist(R_1, R_2, D), D < \delta.$$

Finally, the scratch width hypothesis is derived from the horizontal distance between inferred ridge boundaries:

$$\text{scratch_width}(R_1, R_2, W, P) \leftarrow \text{parallel_ridges}(R_1, R_2, P), h_dist(R_1, R_2, W).$$

Multiple width hypotheses may coexist simultaneously, producing a ranked set of plausible geometric interpretations instead of a single deterministic estimate (see Figure 3). For the running example shown in Figure 2, the reasoning stage infers multiple candidate ridge boundaries and derives competing width hypotheses. The dominant explanation corresponds to a width estimate of $25.80 \mu\text{m}$ associated with the highest possibility degree.

3. Discussion and future work

The presented framework illustrates how symbolic geometric reasoning can complement neural perception for tribological SEM image analysis. Current machine learning approaches in tribology primarily focus on visual classification, segmentation, or feature detection [2]. In contrast, Tribo-AI investigates how high-level geometric measurements may emerge from explicit symbolic reasoning over uncertain visual detections. A central aspect of the framework is the representation of neural outputs through possibility distributions derived from detector confidence values. Instead of treating the CNN predictions as deterministic symbolic facts, the framework preserves graded uncertainty during the symbolic reasoning

process. This provides a connection between the neuro-perceptual stage and the symbolic reasoning layer through possibilistic ASP. From a KR perspective, this enables non-monotonic reasoning over uncertain geometric structures while maintaining explicit reasoning traces and interpretable inference steps.

The experiments suggest that symbolic geometric reasoning may support interpretations that are difficult to obtain directly from standard CNN-based predictors alone. For example, overlapping or layered scratch structures may visually appear as a single region to the neural detector, whereas symbolic geometric relations can support the inference of multiple ridge boundaries and structured scratch compositions. In this sense, the framework does not replace neural perception, but extends it through geometric and relational reasoning grounded in expert knowledge. The current work remains exploratory and presents several limitations. The possibilistic distributions are presently derived from detector confidence scores using heuristic transformations, and the symbolic rules are manually specified from tribological expertise. Moreover, the evaluation currently focuses on prototype-level measurements and interactive expert inspection rather than large-scale quantitative benchmarking.

Future work will investigate principled mechanisms for uncertainty propagation between neural and symbolic components using possibility theory and related uncertainty-aware KR frameworks.

Declaration on Generative AI. During the preparation of this work, the author(s) used GeminiAI, ChatGPT, and Copilot in order to: Grammar and spelling check, Paraphrase and reword, Improve writing style. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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