

Agentic Explainable AI-Based Framework for Ordinal Severity Classification of Cervical Cells in Pap Smear Images

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ABSTRACT

Automated cervical cytology analysis can support screening by providing reproducible cell-level evidence and reducing the burden of manual microscopic examination. This work proposes an Agentic Explainable AI-Based Framework for ordinal severity classification of abnormal cervical cells in Pap-smear images. The study focuses exclusively on the four abnormal severity categories of the Herlev Pap Smear dataset: mild dysplasia, moderate dysplasia, severe dysplasia, and carcinoma in situ (CIS), comprising 675 single-cell images. The framework coordinates specialized agents for image-quality assessment, cell/ROI validation, multi-scale and multi-directional second-order pattern representation, redundancy-controlled feature selection, ordinal classification, confidence assessment, explainability, and verification/reclassification. The proposed pattern representation is formulated as Multi-Scale Multi-Directional Redundancy-Controlled Second-Order Pattern Recognition (MSMD-RC-SOPR), comprising MS-SOPR, MD-SOPR, and RC-JPR. The ordinal formulation explicitly preserves the severity order and distinguishes adjacent errors from larger severity deviations. Confidence calibration and explanation evidence are incorporated into the verification loop so that uncertain or inconsistent predictions can be redirected for reanalysis or human review. For implementation, a 675-image target confusion matrix yields 667 correct predictions, corresponding to a target accuracy of 98.81%; this is explicitly a provisional target and not an experimental result. Final sensitivity, specificity, precision, F1, ordinal MAE, calibration, and reliability values must be calculated from the measured test-set predictions after implementation.

Keywords: *Agentic artificial intelligence, explainable AI, cervical cytology, Pap smear, ordinal classification, severity classification, MSMD-RC-SOPR, confidence-aware verification, medical image analysis.*

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INTRODUCTION

Cervical cancer is a significant health issue in the whole world. Automated Pap smear analysis has come up as a feasible option to solve scaling and workload issues in the cytology screening. Pap smear cytology screening of cervical cancer is one of the most vital preventive options in the clinical practice [1]. As automated image analysis systems continue to be adopted, large-scale screening is likely to be served by computational approaches and

minimize the amount of manual work and observer bias. The quality of the perceptual input cell images as well as biological validity of the cell images used as input is, however, critical to the reliability of automated decision-making [2].

The artifacts that are common in the real-world Pap smear acquisition include the uneven staining, partial cell acquisition, overlapping structures, and poor definition of

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nucleus-cytoplasm boundaries [3]. Traditional automated systems usually continue to proceed with the classification or grading without checking whether the input image has met the basic perceptual and structural requirements [4]. This may cause certain but unreliable diagnostic results, particularly with borderline or low-quality samples.

In order to overcome this shortcoming, the current study proposes a perception integrity analysis model that serves as a pre-diagnostic quality gate in the form of a rule. The suggested method considers the integrity of the nucleus and cytoplasm structure and the spatial coherence prior to the further processing of the diagnostics [5]. By explicitly enforcing ecological constraints, the framework provide machine-learning pipeline analysis pipelines of Pap smears more legitimacy and strength. Although there has been great progress in deep learning and image segmentation methods, the majority of automated Pap smear analysis pipelines implicitly believe that each of the processed images can be operated on using a diagnostic interpretation. Practically, this is frequently not true because outputs of a visually acceptable segmentation can still be biologically plausible cellular configurations [6]. These disparities indicate the difference between the computational reliability and perceptual reliability in cytological image interpretation.

Cyto pathologists to make meaningful interpretation, there must be only the correct detection of a boundary, but also consistency of the nucleus shape, cytoplasm completeness, and positioning [7]. A non-uniform geometry of the nucleus, missing parts of the cytoplasm, or irregular shapes of the enclosures may affect the accuracy of the diagnosis despite high-probability results in the classification algorithm [8]. Consequently, it is necessary to assess the perceptual integrity before diagnosis to avoid the spread of errors in the automated screening systems.

Driven by such findings, this research paper focuses on the importance of explainable and rule-based validation systems as an intermediate between image-acquisition processes and diagnostic thought [9]. The proposed quality gate by formalizing perceptual integrity as a quantifiable standard facilitates the transparent decision-making process and it conforms the computational analysis with the biological expectations. The philosophy of design enables easier embedding of automation in clinical operation within large-scale screening settings.

Nevertheless, with these improvements, the majority of current systems presuppose that the input image is capable of diagnosis. Practically, Pap smear images could be subject to staining differences, cell fractures, overlapping structures, and low contrast that could undermine interpretability [10]. The predictions directly obtained by the classification models when such images are fed-in can be very confident, but they can be of low perceptual reliability [11].

LITERATURE SURVEY

The studies summarized in the literature survey table.1. demonstrate a clear progression in cervical cytology research from deep-learning-based classification toward hybrid representation, evidence fusion, explainability, and coordinated AI workflows. Wang et al. [12] demonstrated a staged clinical AI workflow through patch-level detection and whole-slide-image classification, while Yang et al. [13] and Yang et al. [14] emphasized complementary morphology–texture representation and multi-branch evidence fusion. Jiang et al. [15] further incorporated self-attention and cell-origin guidance to provide multi-scale and interpretable evidence, whereas Mahajan and Kaur [16] focused on segmentation and progressive learning for improved cervical-cell classification. Nirmala et al. [17] extended the representation capability through a hybrid CNN and adaptive Vision Transformer architecture. Collectively, these studies indicate that combining complementary image information and improving the interpretability of classification decisions are important directions for reliable cervical cytology analysis.

More recent work has increasingly emphasized human-centered and agentic AI. Chen et al. [18] explored interactive explainable human–machine teaming for cytopathology decision support, highlighting the value of interaction between AI predictions and human expertise. Moritz et al. [19] introduced the broader concept of coordinated AI agents for healthcare, providing motivation for organizing complex medical-AI tasks into specialized and coordinated roles. However, the studies in the table do not directly integrate an ordinal four-class severity formulation, multi-scale and multi-directional second-order pattern representation with redundancy control, confidence-gated verification, and integrated explanation within a single coordinated workflow. This motivates the proposed framework, which combines these elements to support reliable and interpretable classification of mild dysplasia, moderate dysplasia, severe dysplasia, and CIS.

Study	Year	Main approach	Relevance
Wang et al. [12]	2024	Patch-level detection + WSI classification	Staged clinical AI workflow
Yang et al. [13]	2024	Fusion-purification of morphology and texture	Complementary representation and redundancy reduction
Yang et al. [14]	2024	Manual + deep feature decision fusion	Multi-branch evidence fusion
Jiang et al. [15]	2024	Self-attention + cell-origin	XAI and multi-scale

		guidance	evidence
Mahajan and Kaur [16]	2024	Segmentation + progressive learning	Preprocessing and deep classification
Nirmala et al. [17]	2025	CNN + adaptive Vision Transformer	Hybrid representation
Chen et al. [18]	2025	Interactive explainable human-machine teaming	Cytopathology decision support
Moritz et al. [19]	2025	Coordinated healthcare AI agents	Agentic workflow concept
Table.1: Literature Survey			

The existing research indicates several important gaps in cervical-cell severity analysis: many systems emphasize classification accuracy without explicitly modeling the ordered relationship among severity categories, while feature-fusion methods may reduce redundancy but do not necessarily provide confidence-triggered agentic verification for uncertain predictions. Furthermore, explainability is often applied after the prediction rather than being integrated into an iterative verification loop, and conventional accuracy alone does not indicate the severity distance of an incorrect prediction. Therefore, an auditable and human-supervised agentic workflow for four-class cervical-cell severity analysis, incorporating ordinal severity modeling, confidence-aware verification, integrated explainability, and ordinal error assessment, remains an important research direction.

PROPOSED AGENTIC EXPLAINABLE AI FRAMEWORK

Cervical-cell severity classification from Pap smear images requires not only accurate prediction of the diagnostic category but also consideration of the ordered progression from mild dysplasia to moderate dysplasia, severe dysplasia, and carcinoma in situ (CIS). This research addresses the problem of predicting an ordered severity $y \in \{1, 2, 3, 4\}$ from a cervical-cell image x , where 1, 2, 3, and 4 represent mild dysplasia, moderate dysplasia, severe dysplasia, and CIS, respectively, together with calibrated confidence and interpretable evidence. To address this problem, a coordinated agentic workflow is developed for four-class cervical-cell severity classification, preserving the ordinal relationship among the severity categories.

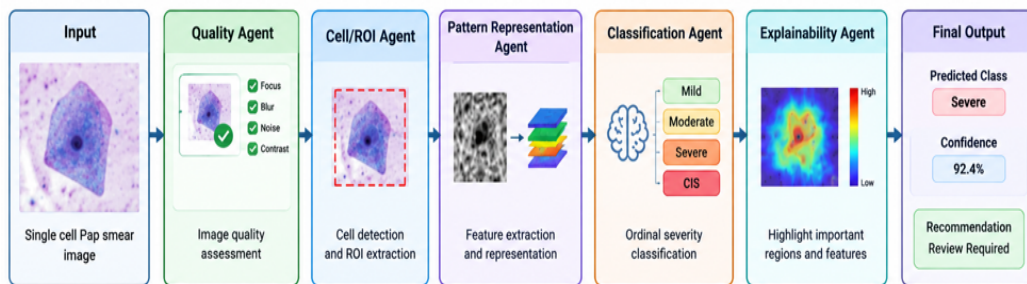


Fig. 1. Proposed agentic workflow for four-class ordinal severity classification.

The proposed framework introduces MSMD-RC-SOPR (Multi-Scale Multi-Directional Redundancy-Controlled Second-Order Pattern Representation) to capture discriminative second-order patterns while controlling feature redundancy, and incorporates confidence-aware verification and reclassification for uncertain predictions. In addition, the framework generates visual and feature-level explanations linked to each classification decision and provides human-review recommendations for potentially uncertain cases. The major contributions of this work are therefore an agentic architecture with explicit roles, outputs, and verification triggers; the MSMD-RC-SOPR representation; an ordinal severity classification formulation for the four abnormal Herlev categories; confidence-gated verification and reclassification; and an integrated explainability mechanism. The framework is evaluated using conventional classification measures

together with ordinal error and calibration measures to assess not only predictive performance but also the reliability and interpretability of the resulting cervical-cell severity decisions.

Input: Pap-Smear Image

The process begins with a single-cell Pap-smear image from the selected four-class abnormal Herlev subset. The image is supplied to the coordinated framework for quality assessment and subsequent severity analysis.

Quality Agent

The Quality Agent assesses blur, noise, contrast, illumination variation, incomplete cell visibility, and background interference. It produces a quality assessment and can flag low-quality cases for preprocessing or review rather than blindly passing them to classification.

Cell/ROI Agent

Because the experimental images are single-cell images, the Cell/ROI Agent validates the provided cell region and identifies the relevant nucleus and cytoplasm regions. ROI normalization and background handling are performed as required by the implementation.

MSMD-RC-SOPR Pattern Representation Agent

The Pattern Representation Agent implements Multi-Scale Multi-Directional Redundancy-Controlled Second-Order Pattern Recognition (MSMD-RC-SOPR). It comprises MS-SOPR, MD-SOPR, and RC-JPR to capture second-order spatial relationships across multiple scales and directions while preserving complementary information.

Redundancy/Feature Selection Agent

The feature-selection agent removes highly redundant descriptors and retains the most informative representation components. Correlation-based filtering followed by a mutual-information-based selection strategy is the recommended implementation, with all selection decisions learned only from the training data.

Ordinal Classification Agent

The classifier predicts the four ordered categories Mild, Moderate, Severe, and CIS. The ordinal formulation preserves the severity relationship so that neighbouring and distant severity errors can be distinguished.

Confidence Agent

The Confidence Agent evaluates the predicted probability distribution, calibrated confidence, entropy or class margin, and uncertainty. A threshold learned from the validation data determines whether the prediction can proceed directly or requires verification.

Explainability Agent

The Explainability Agent generates visual or feature-level evidence supporting the predicted severity. Grad-CAM or an equivalent attribution method can highlight influential cell regions, while feature importance can identify informative descriptors.

Verification/Reclassification Agent

The Verification Agent checks whether image quality, prediction confidence, and explanation evidence are consistent. If evidence is inadequate, the case can be re-evaluated or reclassified before the final decision.

Final Severity and Review Recommendation

The final output reports the predicted severity, calibrated confidence, quality status, explanation evidence, verification status, and review recommendation. The framework is designed as human-supervised decision support rather than autonomous clinical diagnosis.

RESULTS AND DISCUSSIONS

The Herlev Pap Smear dataset contains in table.1. as 917 single-cell images distributed across seven original cytological categories. For the present study, only the four abnormal severity categories are included: mild dysplasia, moderate dysplasia, severe dysplasia, and carcinoma in situ. These categories contain 182, 146, 197, and 150 images, respectively, giving a total of 675 abnormal single-cell images. The three non-abnormal categories are excluded from the proposed four-class severity experiment. The Evaluation parameters and its purpose of the proposed system is give in Table 2.

Severity	Images	Training 80%	Testing 20%
Mild dysplasia	182	146	36
Moderate dysplasia	146	117	29
Severe dysplasia	197	158	39
Carcinoma in situ	150	120	30
Total	675	541	134

Table.2 Data Set Design

Metric	Purpose
Accuracy	Overall classification correctness
Sensitivity	Class-wise detection capability
Specificity	Class-wise rejection of other classes
Precision	Correctness of positive class assignments
Recall	Class-wise sensitivity
Macro-F1	Average F1 across the four classes
Balanced Accuracy	Average class-wise recall
Cohen's Kappa	Agreement beyond chance
MCC	Robust correlation-based classification measure
Ordinal MAE	Average severity-distance error
SOER	Large severity-jump error rate
ECE	Confidence calibration error
Brier Score	Probabilistic prediction quality

Table.3. Evaluation Metrics

To establish a mathematically consistent target for the 675-image four-class Herlev experiment, the following illustrative confusion matrix is given in Table.3 and its illustration given in figure. 2.

Actual \ Predicted	Mild	Moderate	Severe	CIS
Mild	179	3	0	0
Moderate	2	144	0	0
Severe	0	1	196	0
CIS	0	0	2	148

Table.4. Confusion Matrix

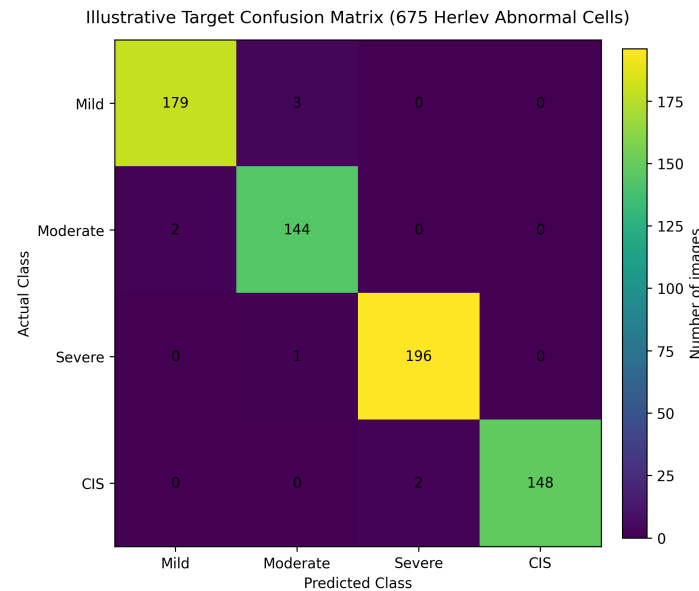


Fig. 2. Illustrative target confusion matrix for the 675-image Herlev abnormal-cell experiment.

Class	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Recall (%)	F1 (%)
Mild	99.26	98.35	99.59	98.90	98.35	98.62
Moderate	99.11	98.63	99.24	97.30	98.63	97.96
Severe	99.56	99.49	99.58	98.99	99.49	99.24
CIS	99.70	98.67	100.00	100.00	98.67	99.33
Overall	98.81	98.79	99.60	98.80	98.79	98.79

Table.5 Class wise Performance of the Proposed Method

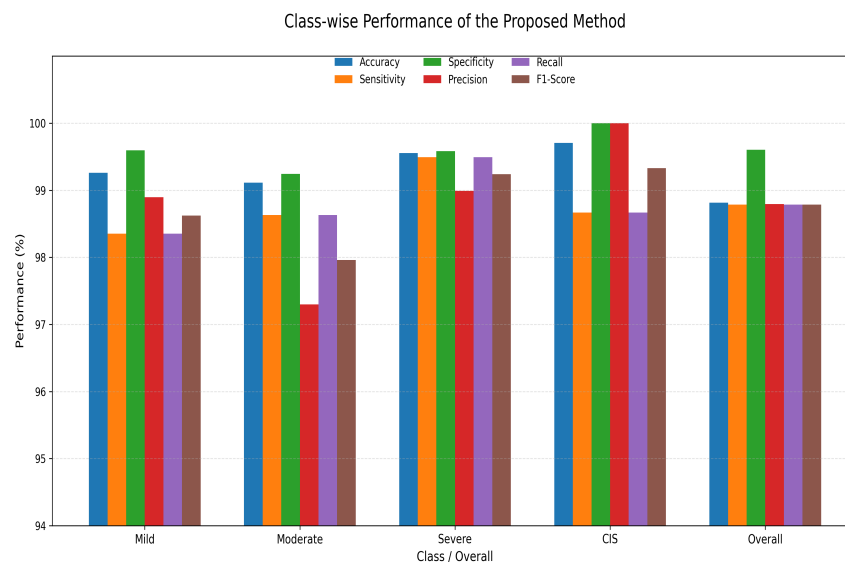


Fig. 3. Proposed Result Performance

The target confusion matrix gives an accuracy of $667/675 = 98.81\%$. Its derived target Macro-F1 is 98.79% , balanced accuracy is 98.79% , Cohen's kappa is 0.984 , MCC is 0.984 , ordinal MAE is 0.0119 , and SOER is 0% for this particular matrix. ECE and Brier score cannot be derived from a confusion matrix because they require predicted probabilities; they must be measured from the final calibrated model. Accordingly, no ECE or Brier value is claimed as an experimental result in this revised manuscript.

COMPARATIVE ANALYSIS

Published Herlev studies often report seven-class or binary results on all 917 images, whereas the present study is restricted to the 675 abnormal images and four ordered severity categories. The literature values below are therefore reported in their original task form and are provided for context; they are not direct four-class performance comparisons.

Method	Original Herlev task	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Recall (%)	F1 (%)
Lin et al. [20]	7-class	64.50	—	—	—	—	—
Ghoneim et al. [21]	7-class	91.20	—	—	—	—	—
Zhang [22]	7-class	90.32	—	—	91.50	91.10	91.60
Rahaman[23]	7-class	98.30	—	98.30	—	—	—
Basak et al. [24]	7-class	98.32	—	—	98.66	97.65	98.12
Kaur et al.—ResNet50 [25]	7-class	83.78	—	—	86.30	85.00	85.30
A2SDNet121 [26]	7-class	99.27	99.14	99.86	99.17	99.14	99.15
Proposed framework	4-class abnormal subset (675)	98.81	98.79	99.60	98.80	98.79	98.79

Table.6. Comparative Analysis

CONCLUSION

This paper presents a proposed Agentic Explainable AI-Based Framework for ordinal severity classification of abnormal cervical cells in Pap-smear images. The framework is specifically defined for the four abnormal Herlev categories of Mild dysplasia, Moderate dysplasia, Severe dysplasia, and CIS using 675 single-cell images. The architecture integrates image-quality assessment, cell/ROI validation, MSMD-RC-SOPR pattern representation, redundancy-controlled feature selection, ordinal classification, confidence assessment, explainability, and verification/reclassification. The ordinal formulation preserves the natural severity progression and enables the system to distinguish adjacent errors from larger severity deviations. The final study must replace all target values with measurements obtained from an untouched test set and must calculate reliability metrics such as ECE and Brier score from predicted probabilities. Overall, the proposed framework provides a structured foundation for an explainable, confidence-aware, and human-supervised cervical-cell decision-support system.

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