УДК 616.24-073.756.8:004.8 doi: 10.36422/23076348-2025-13-3-76-84

The Impact of automated analysis results on decision-making by radiology residents when evaluating solitary pulmonary nodules

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Влияние результатов автоматизированного анализа на принятие решений рентгенологами-стажерами при оценке одиночных легочных очагов

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Summary

Background. The evaluation of solitary pulmonary nodules (SPNs) is a complex diagnostic challenge, particularly for radiology residents, whose limited experience increases the risk of errors. Artificial intelligence (AI) systems are seen as a promising tool to enhance diagnostic accuracy, but their impact on residents' decision-making remains understudied. **Aim.** To investigate the impact of AI-assisted automated analysis of SPNs on the diagnostic accuracy and decision-making processes of radiology residents. **Materials and methods.** A two-phase prospective study involved 4 residents evaluating 100 CT scans without and with AI support (Hiveomics Malignancy Index). The AI classified nodules using a 5-tier malignancy scale. Ground truth diagnoses were confirmed via histopathology, microbiology, and clinical follow-up. **Results.** Without AI, residents' mean accuracy was 43%, with the highest errors in inflammation (17.9%) and tuberculosis (32.1%) detection. AI improved overall accuracy by 8.8% (p=0.0003), notably for malignant neoplasms (+13.4%), but had limited impact on tuberculosis (+3.6%). **Conclusion.** AI significantly enhances malignant SPN diagnosis for radiology residents but requires refinement for complex cases (tuberculosis, hamartomas). The results highlight AI's potential as an educational and clinical decision-support tool.

Keywords: solitary pulmonary nodules, artificial intelligence, automated analysis, computed tomography

Резюме

Обоснование исследования. Оценка одиночных очагов в легких (ООЛ) представляет сложную диагностическую задачу, особенно для врачей-стажеров, чей ограниченный опыт повышает риск ошибок. Интеграция систем искусственного интеллекта (ИИ) рассматривается как перспективный инструмент для улучшения диагностики, однако их влияние на принятие решений рентгенологами-стажерами резидентами изучено недостаточно. **Цель:** исследовать влияние автоматизированного анализа ООЛ с помощью ИИ на диагностическую точность и процесс принятия решений врачами-резидентами. **Материалы и методы.** Проведено двухэтапное проспективное исследование с участием 4 рентгенологов-стажеров, оценивших 100 КТ-сканов без и с поддержкой ИИ (Hiveomics Malignancy Index). ИИ классифицировал узлы по 5-балльной шкале злокачественности. Истинные диагнозы установлены на основе гистологии, микробиологии и клинического наблюдения. **Результаты.** Без ИИ средняя точность участников составила 43%, с наибольшими ошибками при диагностике воспалений (17,9%) и туберкулеза (32,1%). С ИИ общая точность выросла на 8,8% (p=0,0003), особенно для злокачественных образований (+13,4%). Однако влияние на диагностику туберкулеза осталось минимальным (+3,6%). **Заключение.** ИИ значительно улучшает диагностику злокачественных ООЛ у резидентов, но требует доработки для сложных случаев (туберкулез, гамартомы). Результаты подчеркивают потенциал ИИ как вспомогательного инструмента в обучении и клинической практике.

Ключевые слова: одиночные легочные очаги, искусственный интеллект, автоматизированный анализ, компьютерная томография

Introduction

Incidentally detected pulmonary nodules on computed tomography (CT) scans pose a significant clinical challenge, as they necessitate further investigation to differentiate between benign and malignant lesions. This requirement creates substantial ethical and clinical dilemmas: missing a malignant nodule risks cancer progression, while unnecessary intervention for a benign process entails avoidable risks and costs. The evaluation of solitary pulmonary nodules (SPNs) is a complex diagnostic task in radiology. This task is particularly challenging for radiology residents; whose limited interpretive experience heightens the risk of diagnostic errors [1].

To standardize the approach to such findings, clinical guidelines have been developed (e.g., by the British Thoracic Society, Fleischner Society) [2, 3]. However, these guidelines have significant limitations, including:

- a high rate of overdiagnosis and unnecessary invasive procedures (e.g., up to 25% of patients without lung cancer undergo thoracoscopy/VATS based on false suspicion of malignancy, as reported in a major study) [4];
- low patient adherence to long-term surveillance (over 50% of high-risk patients with new nodules fail to undergo recommended, timely follow-up CT scans, as demonstrated by a Toronto study) [5];
- the absence of clear algorithms for patients with a history of extrapulmonary malignancies [2, 3];
- diagnostic uncertainty for nodules measuring 8–30 mm, where the choice between surveillance, biopsy, and PET remains ambiguous [3];
- failure to account for the risk of tuberculosis and other granulomatous diseases in endemic regions.

The integration of artificial intelligence (AI) systems capable of automatically detecting nodules, assessing their characteristics, and predicting malignancy risk is viewed as a promising tool to overcome these limitations and support decision-making [6–8]. The problem is especially relevant for young radiologists who, for one reason or another, cannot get a second opinion from senior colleagues on a specific clinical case. This creates the preconditions for integrating technology into the educational process [9].

Although the accuracy of such systems in classification tasks matches or exceeds that of experienced radiologists, the critical question for clinical implementation is not the absolute accuracy of AI itself, but its actual impact on physician decision-making in an assistive role. Large-scale studies demonstrate that this impact varies widely, from significant improvement to deterioration in diagnostic performance [10, 11]. Notably, traditional factors (radiologist experience, prior AI exposure) proved unreliable predictors of how effectively an individual radiologist integrates AI prompts into their workflow. This highlights the risks of both uncritically accepting erroneous AI recommendations and disregarding accurate prompts due to insufficient confidence or a lack of understanding of the algorithm.

At the same time, innovative technologies for the early diagnosis of pathological processes in the lungs, along with psychological predictors of the disease, play a key role in the success of subsequent treatment [12] and the quality of life of patients. Despite the acknowledged importance of the problem, the influence of automated analysis results specifically on the diagnostic decisions and confidence of radiology residents remains insufficiently studied. The present research aims to address this gap.

Materials and methods

Study aim: to investigate the impact of implementing automated lung nodule analysis systems in CT imaging on the diagnostic performance and decision-making processes of radiology residents.

Study Design. This was a prospective, two-phase, observer performance study conducted to assess the diagnostic utility of an AI-based tool (Hiveomics Malignancy Index) for classifying solitary pulmonary nodules (SPNs) on non-contrast chest CT. The performance of radiology residents was evaluated before and after exposure to AI system outputs.

Participants. A total of 100 chest CT scans from asymptomatic adult patients (mean age, 57.6±15.3 years; range, 15–86 years; 42 males [42%], 58 females [58%]) with incidentally detected solitary pulmonary nodules measuring 8–30 mm were included (Fig. 1). Patients with known malignancy or granulomatous disease, multiple nodules, or archival imaging were excluded.

Nosological distribution:

- malignant neoplasm — 54%;
- benign lesion of unknown nature — 3%;
- hamartoma — 15%;
- tuberculosis — 21%;
- nonspecific inflammatory process — 7%.

Image acquisition. Chest CT examinations were obtained from 30 different scanners across multiple vendors (GE, Siemens, Toshiba, Philips) with slice thicknesses ranging from 1.0 to 3.0 mm. Images were reconstructed using standard algorithms in 95% of cases and high-resolution kernels in 5% of cases.

Study procedure. In **Phase I**, four radiology residents independently reviewed the 100 CT scans without AI support and assigned each patient to one of two categories: benign or malignant nodules, using predefined criteria. They then provided a more specific diagnosis based on the nosological classification.

Following Phase I, the Hiveomics Malignancy Index system processed all 100 CT scans. The AI model successfully detected and analyzed nodules in 98 of 100 cases (98%). In two cases, no lesion was identified.

In **Phase II**, four radiology residents re-reviewed the same 100 CT scans with full access to the Hiveomics Malignancy Index AI outputs. Residents could either maintain their initial diagnosis or revise it based on the AI system's suggestions.

Ground truth diagnoses were established using clinical follow-up, imaging progression, histopathology, or microbiological data. Verification breakdown: clinical/radiologic (63%), histopathology (19%), etiologic confirmation (18%). Final diagnoses included:

- adenocarcinoma — 26%;
- hamartoma — 15%;
- carcinoid — 10%;
- tuberculosis — 21%;
- pneumonia — 7%;
- squamous cell carcinoma — 9%;
- myofibroblastic tumor — 2%;
- metastases — 7%;
- large intrapulmonary lymph node — 1%;
- retention cyst — 2%.

AI System Description. The Hiveomics Malignancy Index is a deep learning algorithm that performs automated

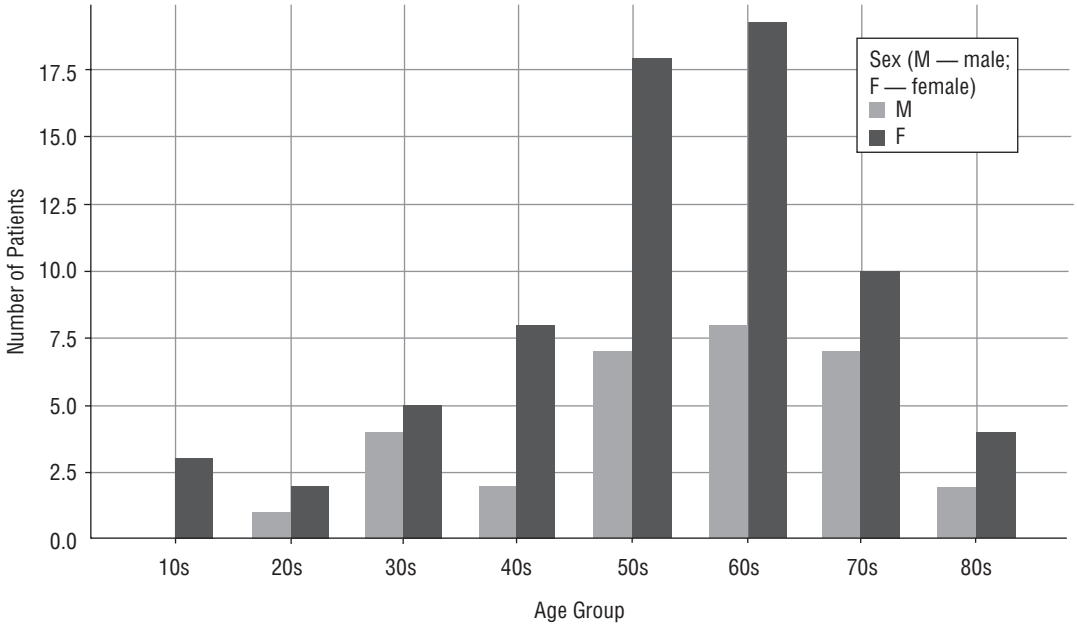

Fig. 1. Distribution of patients by age and sex

detection, segmentation, and classification of pulmonary nodules (8–30 mm) on non-contrast CT scans in DICOM format. Outputs included nodule size, consistency (solid, part-solid, or non-solid), malignancy probability (on a 5-tier scale), and differential diagnosis suggestions for benign lesions.

AI probability tier definitions. To facilitate clinical interpretation, the continuous malignancy score is categorized into five tiers, each reflecting a distinct level of certainty:

1. **Benign (Category 1):** virtually no risk of malignancy (error rate ≤ 1%), ideal for safely ruling out cancer.
2. **Probably benign (Category 2):** low risk (error rate ≤10%); these nodules can be followed with routine surveillance.
3. **Indeterminate (Category 3):** equivocal findings where the algorithm's confidence is insufficient to guide a definitive decision; additional clinical or imaging data may be required.
4. **Probably malignant (Category 4):** elevated risk (error rate ≤10%), prompting consideration of further diagnostic workup (e.g., PET, biopsy).
5. **Malignant (Category 5):** high risk (error rate ≤1%), warranting expedited evaluation and management.

These tiers provide a structured risk framework that complements the malignancy index categories, empowering clinicians to tailor patient management based on both quantitative and categorical AI outputs.

The table below (Tab. 1) summarizes the AI's classification performance across the five malignancy index tiers, highlighting both the accuracy within each category and the corresponding interpretation of diagnostic confidence.

In addition to the malignancy-index categories, the system's performance was also stratified by specific lesion etiology (Tab. 2).

Table 1

Performance by Malignancy index categories

Category	Interpretation	Accuracy (%)
1	High probability benign	100
2	Probably benign	89
3	Indeterminate (no clear assignment)	Not reported
4	Probably malignant	87.5
5	High probability malignant	100

Note: The indeterminate Category 3 represents those nodules for which the AI could not decisively favor benign or malignant. Accuracy was not calculated for this intermediate stratum.

Table 2

Accuracy for key lesion types

Diagnosis	Accuracy, %
Hamartoma	91.2
Tuberculosis	84.6

Outcomes and statistical analysis

Metrics:

- overall accuracy: proportion of correct diagnoses across all cases and categories;
- class-specific accuracy: proportion of correct diagnoses within each diagnostic category;
- overdiagnosis (false positives, FP) and underdiagnosis (false negatives, FN) for malignant neoplasms and tuberculosis, reported as counts and percentages.

Formulas:

$FP\% = (FP / TN) \times 100$, where TN is the number of true-negative cases for the given class.

$FN\% = (FN / TP) \times 100$, where TP is the number of true-positive cases for the given class.

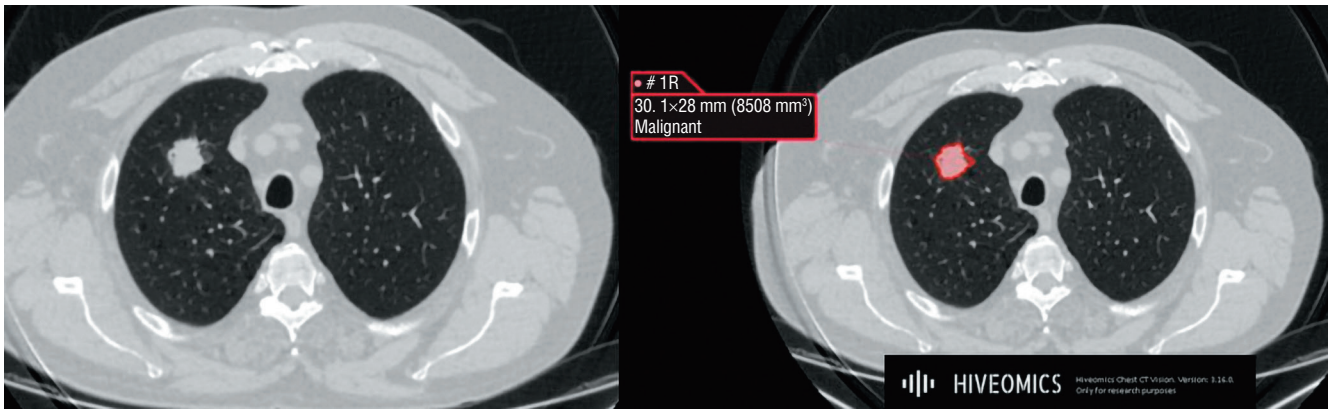

Fig. 2. Example of the Hiveomics malignancy index system operation: Demonstrating a solid-type nodule in the upper lobe of the right lung on CT (lung window). The system classified it as malignant (Category 5). Histologically confirmed as squamous cell carcinoma of the lung

To assess the statistical significance of changes in diagnostic accuracy after AI implementation, the McNemar exact test—a nonparametric criterion for paired dependent data—was applied.

The primary outcome was the diagnostic accuracy before and after the implementation of AI support. Secondary outcomes included overdiagnosis and underdiagnosis of malignancy and tuberculosis. The McNemar exact test was used to assess the statistical significance of performance differences between phases. Analyses were performed using paired data.

Exclusion criteria

Cases with nodules <8 mm or >30 mm, multiple nodules, diffuse lung involvement, or characteristic tree-in-bud patterns were excluded.

Results

Table 3 presents the diagnostic accuracy of four resident physicians in differentiating solitary pulmonary nodules (SPN) using CT without artificial intelligence (AI) systems. The overall mean diagnostic accuracy was 43.0% (range, 33.0–49.0%). The highest accuracy was observed for malignant neoplasms (MN) (mean 51.9%). The greatest diagnostic challenges occurred with non-specific inflammatory processes (mean 17.9%). Accuracy for tuberculosis (mean 32.1%) and hamartoma (mean 38.3%) also remained low. Significant inter-observer variability was noted (e.g., tuberculosis: 14.3–47.6%; hamartoma: 13.3–60.0%). These data demonstrate substantial limitations in visual SPN assessment, particularly for benign processes, and critically low accuracy in recognizing inflammation (<20%).

This table highlights the significant constraints of visual SPN assessment by residents, especially for benign processes (tuberculosis, hamartoma), and reveals critically low accuracy for non-specific inflammation identification (<20%) without AI or auxiliary tools (advanced image analysis, PET/CT). Key issues include low overall accuracy (43%), extremely poor nonspecific inflammation detection (17.9%), and substantial inter-observer variability. These findings align with established literature, underscoring the need for standardized approaches (e.g., Fleischner Society or Lung-RADS algorithms), follow-up imaging, advanced modalities (such as PET/CT), and AI-assisted diagnostic systems (CADx) to improve differential diagnosis accuracy, particularly for complex benign cases, and reduce unnecessary interventions.

Table 4 details diagnostic errors for MN and tuberculosis. On average, 36.4% of benign nodules were misclassified as malignant (overdiagnosis; range, 26.1–47.8%), confirming the observed trend in Table 3. Conversely, 48.1% of true malignant nodules were missed, resulting in underdiagnosis (range, 27.8–63.0%), indicating significant failure in cancer detection. For tuberculosis, 67.9% of true cases were misclassified (range 52.4–85.7%), directly

Table 3

Accuracy of pathology characterization without artificial intelligence systems

Resident	Accuracy, %	Accuracy in detecting malignant neoplasms, %	Accuracy in detecting tuberculosis, %	Accuracy in detecting hamartoma, %	Accuracy in detecting non-specific inflammatory process, %
Resident 1	47.0	57.4	38.1	46.7	14.3
Resident 2	49.0	72.2	14.3	33.3	14.3
Resident 3	43.0	37.0	47.6	60.0	28.6
Resident 4	33.0	40.7	28.6	13.3	14.3
Average value	43.0	51.9	32.1	38.3	17.9

Table 4

Quantity and percentage of false positives and false negatives for malignant neoplasms and tuberculosis without AI

Resident	Overdiagnosis malignant neoplasms, abc.	Overdiagnosis malignant neoplasms, %	Hypodiagnostics malignant neoplasms, abc.	Hypodiagnostics Malignant neoplasms, %	Overdiagnosis tuberculosis, abc.	Overdiagnosis tuberculosis, %	Hypodiagnostics tuberculosis, abc.	Hypodiagnostics tuberculosis, %
Resident 1	12.0	26.1	23.0	42.6	5.0	6.3	13.0	61.9
Resident 2	22.0	47.8	15.0	27.8	3.0	3.8	18.0	85.7
Resident 3	12.0	26.1	34.0	63.0	15.0	19.0	11.0	52.4
Resident 4	21.0	45.7	32.0	59.3	13.0	16.5	15.0	71.4
Average value	16.8	36.4	26.0	48.1	9	11.4	14.3	67.9

Table 5

Changes in average diagnostic accuracy following AI implementation

Category	Without AI, %	With AI, %	Δ, %
Overall Accuracy	43.0	51.8	8.8
Malignant Neoplasm (MN)	51.9	65.3	13.4
Tuberculosis	32.1	35.7	3.6
Hamartoma	38.3	40.0	1.7
Non-specific Inflammatory Process	17.9	28.6	10.7
Benign Nodule of Indeterminate Nature	41.7	33.3	–8.3

explaining its low diagnostic accuracy (32.1%). Tuberculosis overdiagnosis was substantially lower (mean 11.4%, range 3.8–19.0%), reflecting reduced clinical suspicion compared to MN.

Significant inter-observer variability persisted (e.g., MN underdiagnosis: 27.8–63.0%; tuberculosis underdiagnosis: 52.4–85.7%), confirming experience-dependent subjectivity. These results reveal a dual diagnostic problem: overdiagnosis of MN coupled with underdiagnosis of tuberculosis and MN itself. Collectively, our findings corroborate extensive literature on the extreme difficulty of SPN classification (benign vs. malignant), as summarized in Fleischner Society guidelines.

During Stage 2, all residents received CT analysis results from the Hiveomics Malignancy Index system, were informed about its diagnostic accuracy metrics, and reassessed the etiology of detected nodules. They could either maintain their initial diagnosis or modify it based on input from AI.

Paired comparison (McNemar's exact test) revealed a statistically significant 8.8% increase in overall diagnostic accuracy after AI implementation (p=0.0003). The most substantial improvement occurred in malignant neoplasms (Δ=+13.4%; p-FDR=0.000192). No statistically significant changes were observed for other nosological categories.

Figure 3 illustrates the diagnostic accuracy gains achieved across various pathological processes with the aid of AI.

Results confirm the efficacy of AI-assisted diagnosis (CADx) in improving the classification accuracy of solitary pulmonary nodules (SPN), particularly for malignant and inflammatory lesions, categories with the highest clinical stakes and baseline error rates. While tuberculosis diagnosis showed limited improvement (persistent underdiagnosis remains an issue), the significant increase in accuracy for malignant neoplasms (+13.4%) and overall diagnostic performance (+8.8%) demonstrates AI's potential to reduce critical diagnostic errors. The decreased accuracy for 'benign nodules of indeterminate nature' suggests an AI-driven shift in diagnostic focus toward more specific etiologies.

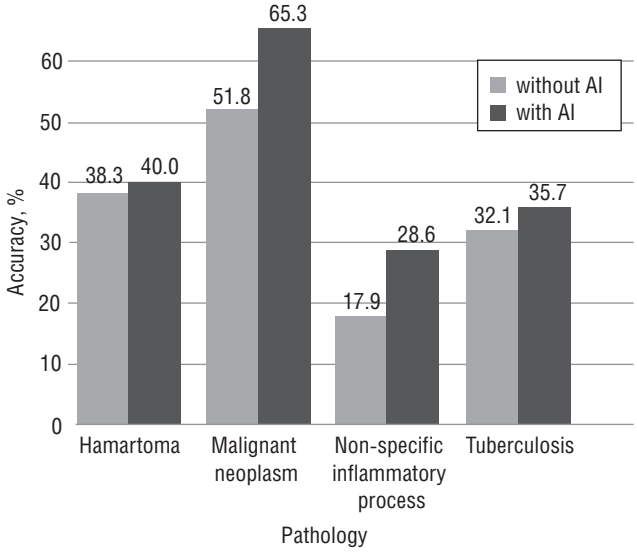

Fig. 3. Dynamics of mean diagnostic accuracy across nosologies following AI implementation

The implementation of AI led to a significant reduction in:

- overdiagnosis of malignant neoplasms (–7.1 pp);
- underdiagnosis of malignant neoplasms (–13.4 pp).

For tuberculosis, underdiagnosis decreased only marginally (–3.6 pp) and remains critically high (64.3%).

Thus, AI-assisted systems (CADx) demonstrated high efficacy in optimizing the diagnosis of malignant neoplasms, significantly reducing the risks of both false-positive and false-negative results. However, their impact on tuberculosis detection was limited, requiring further algorithm refinement or the integration of complementary diagnostic approaches.

The AI system demonstrated the highest efficacy for correcting diagnoses of malignant neoplasms (57.4% accurate corrections) and non-specific inflammatory processes (55.6%). This clinical significance is heightened given the substantial risks of overdiagnosis and underdiagnosis associated with these conditions. However, for tuberculosis and hamartoma, the AI frequently prompted erroneous corrections (33.3% and 30.0% respectively), proving more detrimental than beneficial.

Table 6

Quantities and percentages of false positives and false negatives for malignant neoplasms and tuberculosis with AI

Category	Without AI	With AI	Δ
Overdiagnosis malignant neoplasms, abc.	16.8	13.5	–3.3
Overdiagnosis malignant neoplasms, %	36.4%	29.3%	–7.1
Hypodiagnostics malignant neoplasms, abc.	26	18.8	–7.3
hypodiagnostics malignant neoplasms, %	48.1%	34.7%	–13.4
Overdiagnosis tuberculosis, abc.	9	6.8	–2.3
Overdiagnosis tuberculosis %	11.4%	8.5%	–2.9
Hypodiagnostics tuberculosis, abc	14.3	13.5	–0.8
Hypodiagnostics tuberculosis, %	67.9%	64.3%	–3.6

Table 7

Frequency and Accuracy of Diagnosis Changes After AI Implementation

Diagnosis	Total Changes	Corrected to Right Diagnosis	Changed to Wrong Diagnosis	Correct Changes, %	Incorrect Changes, %
Malignant Neoplasm	68	39	10	57.4	14.7
Tuberculosis	24	11	8	45.8	33.3
Hamartoma	20	7	6	35.0	30.0
Non-specific Inflammatory Process	9	5	2	55.6	22.2

Thus, this AI system functions most reliably as a verification tool for malignant processes. Its application when tuberculosis, hamartoma, or indeterminate benign nodules are suspected warrants caution and requires supplementary validation methods.

The impact of AI varied across physicians (improvement range: 3–17%), likely reflecting differential levels of trust. Nevertheless, it reduced inter-observer variability in error rates (Figure 4).

Currently, the potential applications of AI technology in a specialist's work have not been fully explored. The data presented in the study confirm the hypothesis that AI influences the decision-making of a resident. In addition, progress in the quality of decisions was made and a decrease in the number of errors was noted in all parameters, for all indicators studied, which makes the format of interaction between AI and a resident interesting for increasing the level of knowledge in general. This approach is particularly evident in the work of AI, which demonstrates a high level of accuracy and specificity, currently in development and requiring further refinement.

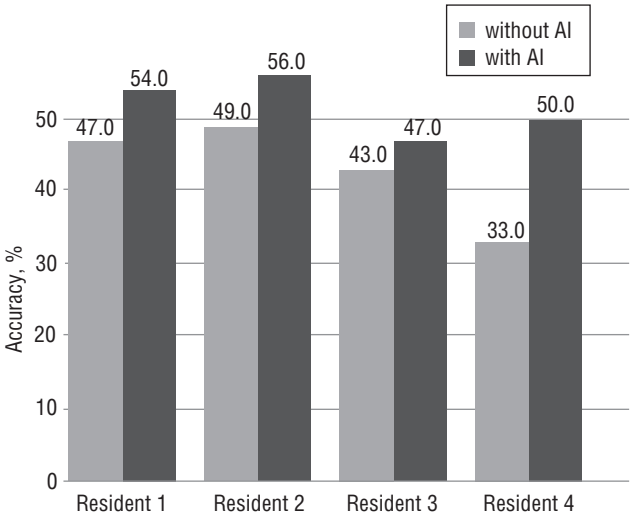

Fig. 4. Aggregate accuracy changes among residents

Limitations of the Study

The study was conducted exclusively with radiology residents who had not yet completed their medical accreditation. Their limited clinical experience may have influenced the results, as their diagnostic performance and decision-making processes might differ significantly from those of experienced radiologists.

Further research is needed to evaluate the impact of AI assistance on board-certified radiologists with varying levels of expertise.

The physicians provided a binary response (benign/malignant), while the AI system used a 5-tier malignancy scale, including an "indeterminate" category. This discrepancy in evaluation methods may have affected the comparability of results.

The AI's ability to abstain from definitive classification in uncertain cases could have introduced bias, as residents were forced to make a binary choice even when unsure.

The residents were informed about the AI's imperfect accuracy, which might have influenced their trust in the system and their willingness to adjust diagnoses based on its suggestions.

The study did not account for potential variability in how individual residents weighed AI recommendations against their own judgments.

The results highlight the need for additional studies involving experienced radiologists to determine whether the observed improvements in diagnostic accuracy are replicable across different skill levels.

Future studies should also explore the impact of AI on older physicians, who may exhibit different patterns of interaction with technology.

Conclusions

1. Visual assessment of SPNs without AI support carries substantial risks: overdiagnosis of malignant neoplasms (mean 36.4%) leading to invasive procedures, and underdiagnosis of life-threatening conditions — tuberculosis (67.9%) and malignant neoplasms themselves (48.1%) — potentially delaying critical treatment.

2. The demonstrated low overall diagnostic accuracy (43.0%) and the systematic nature of clinically significant errors necessitate integrating advanced imaging (PET/CT), strict adherence to diagnostic guidelines (Fleischner Society), and the implementation of AI-assisted systems (CADx) to enhance the reliability of SPN classification.

3. AI implementation (CADx) significantly enhanced malignant neoplasm diagnosis (+13.4% accuracy) by reducing both underdiagnosis and overdiagnosis, thereby mitigating risks of delayed treatment and unwarranted interventions. However, the current level of specificity and accuracy of developed programs remains a fairly high risk of missing a pathology during the individual work of the AI.

4. AI showed minimal impact on tuberculosis detection (underdiagnosis persists at 64.3%, accuracy +3.6%), underscoring the need for pathology-specific algorithm refinement

5. The teamwork of AI and residents showed a more effective diagnostic result than working separately and can be used as a mechanism to improve the quality of resident work.

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Поступила в редакцию 08.08.2025 г.

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