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Review

Artificial intelligence-based computer vision in Polish diagnostic radiology: Image interpretation, performance and national implementation

Praveen Malik

Medical University of Lodz, Poland

Address for correspondence:

Dr. Praveen Malik
Uniwersytet Medyczny w Łodzi
e-mail: pmuk2008@yahoo.co.uk

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ABSTRACT

INTRODUCTION: Computer vision is a clinically deployed component of diagnostic radiology, supporting detection, classification/triage, and segmentation/quantification. International evidence is substantial but concentrated in high-resource systems, with a gap between technical accuracy and clinical utility. Poland launched a nationally coordinated diagnostic artificial intelligence (AI) rollout in 2025–2026 but is under-represented in this literature. This review summarises computer vision performance across main diagnostic tasks and describes Poland's implementation context, centred on the Platforma Usług Inteligentnych (PUI).

METHODS: A narrative review, reported in line with SANRA criteria, of PubMed/MEDLINE, Google Scholar, and Polish institutional and grey-literature sources published 2022–2026.

RESULTS: Detection, classification/triage, and segmentation/quantification are best validated in chest, neurological, and breast imaging, largely overlapping with PUI's five prioritised domains (chest computed tomography (CT), chest radiograph, mammography, brain CT/magnetic resonance imaging, skeletal radiograph). Clinical utility and outcome evidence remains scarcer than accuracy data. PUI is funded through the EU-backed Krajowy Plan Odbudowy; vendors were selected in all five model areas, but routine production use after the 30 June 2026 deadline was unconfirmed (as of 19 October 2026). PUI responds to workload growth and regional and subspecialty distribution among fewer than 4,600 radiologists (about 123 per million; EU average 127), not to a per-capita deficit. In a national survey, 4.7% of institutions used AI, 33.9% of them in CT. Published Polish evidence on diagnostic AI remains limited.

CONCLUSIONS: PUI enters a technically well-evidenced field but is a live test of the under-studied validation gap, offering Polish radiology a substantial opportunity to contribute original evidence.

KEYWORDS

artificial intelligence, computer vision, deep learning, diagnostic imaging, machine learning, Poland, radiology

INTRODUCTION

Computer vision, in the form of deep convolutional neural networks and, increasingly, transformer-based architectures, has moved from a research curiosity to a clinically deployed component of diagnostic radiology. Its core task in this setting is image interpretation: detecting, localising, classifying, and quantifying findings on radiographs, computed tomography (CT), and magnetic resonance imaging (MRI), then presenting the result to the radiologist as a second reader, a triage flag, or a quantitative measurement [1,2,3]. Systematic and scoping reviews published in 2025 confirm that the volume of evidence on diagnostic performance is now

substantial across chest imaging, neuroimaging, and oncological applications, and that the proportion of CE-certified products with peer-reviewed evidence rose from 36% to 66% between 2020 and 2023 [4,5]. At the same time, the same reviews converge on a common finding: technical and diagnostic-accuracy evidence (efficacy levels 1–2) remains far more abundant than evidence on clinical decision-making, patient outcomes, or health-system impact (levels 3–6) [4,5]. This is often described as the “validation gap” between an algorithm performing well on a curated test set and the same algorithm performing reliably, safely, and equitably inside a specific radiology department, on a specific case-mix, read by a specific radiologist [6].

This gap is not evenly distributed across countries. The great majority of external validation studies, multicentre benchmarks, and radiologist-artificial intelligence (AI) comparison trials originate from a small number of health systems in North America, Western Europe, and East Asia [4,5]. Poland, despite operating a national digital health infrastructure coordinated by a dedicated state agency [7], has limited representation in this literature relative to the scale of its national AI rollout. This is a notable gap, because 2025–2026 has been the period in which computer-vision-based diagnostic AI moved from pilot projects to a nationally coordinated rollout in Poland: the Centrum e-Zdrowia (CeZ, the Polish e-Health Centre) is implementing a national Platforma Usług Inteligentnych (PUI, “Intelligent Services Platform”) that will give radiologists across the country access to certified AI models for lung cancer detection on CT, ischaemic and haemorrhagic stroke detection on brain CT/MRI, fracture detection on radiographs, and pathology detection on mammography and chest radiographs, funded through the EU-backed Krajowy Plan Odbudowy (KPO, National Recovery Plan) [7,8,9,10,11]. This is precisely the kind of large-scale, real-world, radiologist-facing deployment that the international literature says is under-evidenced everywhere – and Poland has almost no published voice in describing it.

Alongside the national Platforma Usług Inteligentnych (PUI), Poland has also developed disease-specific AI research initiatives. One example is AI4AR, an OPI PIB (Ośrodek Przetwarzania Informacji – Państwowy Instytut Badawczy, or National Information Processing Institute) project that combines machine-learning analysis of prostate multiparametric MRI with structured reporting, radiologist decision support, and an educational platform based on annotated reference datasets [12]. Although AI4AR is independent of the PUI programme, it illustrates the growing domestic capacity for developing clinically oriented computer-vision solutions in radiology.

Rationale and aim of the review

The scientific rationale for this review is the mismatch described above: computer vision for diagnostic image interpretation is now a well-evidenced field internationally, concentrated in domains (chest, neuro, breast imaging) that largely overlap with the five domains Poland has chosen for its first nationally coordinated AI rollout (the remaining domain being skeletal trauma radiography), yet Polish radiology has limited representation as a subject of that literature relative to the scale of its national rollout, despite the rollout itself being a live, large-scale, radiologist-facing implementation of the kind the international evidence base says is under-studied everywhere. This review therefore has two specific aims. Aim 1: to summarise current evidence on computer vision performance and image interpretation across the diagnostic tasks most relevant to reporting practice – detection, classification/triage, and segmentation/quantification – with particular attention to external validation and the technical-clinical validation gap. Aim 2, and central to the novelty of this review, is to describe in detail the Polish implementation context: the PUI programme and its diagnostic scope, the national survey of radiologists' experience with and attitudes toward AI, adoption figures from CeZ's national digitalisation survey, the workforce pressures that make AI-assisted triage attractive, and the early single-centre experience already reported from Polish hospitals. Poland's position – a health system under radiologist workforce pressure (rising workload and uneven regional and subspecialty distribution), a centrally coordinated rather than market-driven AI rollout, and a hard 2026 funding deadline – makes it a distinctive and currently unpublished case study for how diagnostic computer vision is actually adopted at national scale, as opposed to how it performs in a benchmark paper.

Two recent Polish-authored reviews have surveyed the broader landscape of AI applications in medical imaging and image processing [13,14], offering valuable technical syntheses of algorithms and clinical use cases across imaging modalities. This review takes a complementary but distinct approach: rather than surveying the field broadly, it focuses specifically on how that international evidence base maps onto Poland's national, radiologist-facing AI rollout – a health-system-level implementation lens that has not yet been the subject of a dedicated review.

METHODS

This is a narrative review, not a systematic review, and no formal protocol was registered. Reporting follows the SANRA (Scale for the Assessment of Narrative Review Articles) criteria, including explicit justification of the review's importance and aims (above), a described literature search strategy, evidence-based reasoning, and appropriate presentation of data through

structured sections and a summary table [15]. A structured search was conducted in PubMed/MEDLINE, Google Scholar, and the grey literature of Centrum e-Zdrowia, the Polish Ministry of Health, and Polish radiological and hospital sources, covering material published between 2022 and 2026, with an emphasis on 2025–2026 publications reflecting the most current evidence and the timing of the PUI rollout. The last search was run on 19 October 2026. A small number of key sources published before 2022 were retained deliberately because they are not substitutable: the SANRA scale [15] (2019), which defines the reporting standard followed here, and an early, domain-specific demonstration of deep learning reconstruction in a stroke imaging protocol [16] (2021), which concerns one of PUI’s prioritised domains and illustrates the reconstruction-stage applications discussed in Section: Computer vision across diagnostic tasks. Information on PUI and on the regulatory timeline reflects publicly available sources up to 19 October 2026. Search terms combined “artificial intelligence,” “computer vision,” “deep learning,” or “convolutional neural network” with “radiology,” “diagnostic accuracy,” “image interpretation,” “external validation,” or “radiologist,” and, for the Polish context, “Polska,” “radiolog,” “Centrum e-Zdrowia,” and “Platforma Usług Inteligentnych.” Reference lists of identified reviews were hand-searched. Only sources in English and Polish were included. As a narrative rather than systematic review, article selection and synthesis reflect the author’s judgement of relevance and quality rather than a reproducible screening protocol.

RESULTS

Computer vision across diagnostic tasks

Diagnostic computer vision in radiology performs three broadly distinct tasks, and the maturity of evidence differs across them (Figure 1).

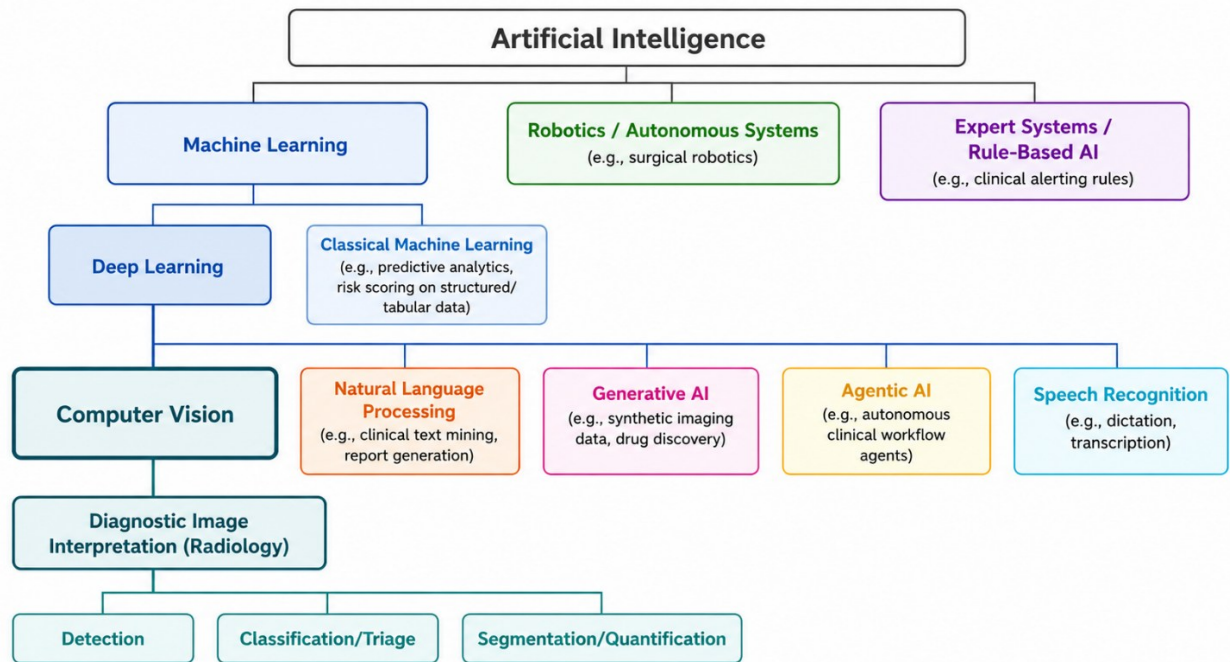


Figure 1. Computer vision within the broader AI hierarchy in medicine, shown alongside related AI subfields – machine learning, robotics/autonomous systems, expert systems, natural language processing, generative AI, agentic AI, and speech recognition – for context. Only the computer vision branch is expanded further, to show the diagnostic image-interpretation tasks in radiology addressed in this review. Colour indicates AI subfield family: blue = machine learning branch (deep learning/classical ML); green = robotics/autonomous systems; purple = expert systems/rule-based AI; orange = natural language processing; pink = generative AI; amber = agentic AI; cyan = speech recognition; teal (bold) = computer vision and its diagnostic image-interpretation applications in radiology, the focus of this review.

Detection and localisation

The best-studied task is flagging a finding and marking its location – a pulmonary nodule, an intracranial haemorrhage, a fracture line. Detection algorithms are typically evaluated against sensitivity, specificity, and free-response operating characteristic curves compared with radiologist reads [4,6]. A 2025 study illustrates both the promise and the nuance of this comparison: a deep-learning model combining airway segmentation with a convolutional classifier for detecting radiolucent foreign-body aspiration on chest CT outperformed three experienced radiologists on recall (71.4% vs. 35.7%) and F1 score (74.1% vs. 52.6%) in a blinded evaluation cohort, while the radiologists retained a higher precision with zero false positives [17]. This pattern – AI substantially reducing missed findings at some cost to specificity, in a task that is difficult precisely because the finding is subtle – recurs across detection literature [1,17] and is one reason detection tools are increasingly framed as concurrent or second readers rather than autonomous decision-makers.

Classification and triage

A second task is assigning a study, or a specific finding within it, to a category: normal/abnormal, malignant/benign, large-vessel-occlusion present/absent. These outputs are used less to make a diagnosis outright and more to re-order the radiologist's worklist, moving studies with a high AI-predicted probability of a critical finding to the top of the queue. This is the task most directly tied to workforce pressure: Poland's radiologist workforce pressure (detailed in Section: The Platforma Usług Inteligentnych (PUI)) sits alongside a broader mismatch between rising imaging workload and radiologist headcount identified across European health systems, and is explicitly cited as a driver for AI-assisted triage in the international literature [2,18].

Segmentation and quantification

The third task, increasingly important in oncological and neurological imaging, is drawing a boundary around a structure or lesion and deriving a quantitative measurement – tumour volume, stroke core and penumbra volume, coronary calcium score. Quantification tasks tend to have the most direct link to reporting: rather than replacing radiologist interpretation, they replace a manual measurement step, reducing inter-reader variability. In some settings, quantification outputs already function as direct clinical decision inputs rather than reporting aids alone – stroke core and penumbra volumes, for instance, are used to determine thrombectomy eligibility – representing a stronger and more directly outcome-linked form of clinical utility than most detection or triage applications have yet demonstrated.

Across all three tasks, recent reviews converge on where the evidence is strongest and weakest. A 2025 rapid systematic scoping review of 140 studies on AI for diagnostics in radiology practice found the great majority of the literature addresses either perceptions of AI (74 studies) or technical effectiveness (53 studies), while only 7 studies actually evaluated implementation and 6 addressed cost – meaning the “does it work in the reading room, at scale, over time” question is answered far less often than “does it perform well in a validation set” [4]. A 2025 mapping of 173 CE-certified radiological AI products found that while the proportion with any peer-reviewed evidence rose from 36% to 66% between 2020 and 2023, the proportion of studies addressing higher-efficacy levels – clinical decision-making, patient outcomes, health-system impact – remained flat at around 24% [5]. Polish authors have contributed directly to this critical literature: a 2025 review from a Kraków-based multi-institutional group (Jagiellonian University Medical College, AGH University of Kraków, Łódź University of Technology, Silesian University of Technology) surveyed AI-empowered radiology and found that neuroimaging and chest imaging, and CT and MRI modalities specifically, dominate current AI product development, aligned with

high-prevalence conditions such as lung cancer, stroke, and breast cancer – largely overlapping with the diagnostic domains that Poland’s own national rollout has chosen to prioritise (which additionally include skeletal trauma radiography) [13,14]; a further 2025 review from Polish authors reached similar conclusions specifically for pulmonary disease diagnosis [19]. Beyond review literature, primary Polish studies now exist across all three task categories described above: a Medical University of Silesia group has developed and externally validated a deep-learning model for detecting foreign objects on chest radiographs (detection) [20], a localisation and measurement model for endotracheal tube positioning relative to the tracheal carina, evaluated on an external validation subset (localisation/measurement) [21], and a deep-learning pipeline for automated cardiothoracic ratio calculation and cardiomegaly detection trained and tested on 8,000 Polish chest radiographs (quantification) [22] – together indicating that Polish-origin peer-reviewed evidence, while still limited relative to PUI’s scale, is not entirely absent.

Image reconstruction and anatomical modelling, upstream of interpretation

Detection, classification/triage, and segmentation/quantification all operate on an image that has already been reconstructed – they interpret pixels a scanner has already produced. Computer vision is also applied earlier in the pipeline, to generate or transform the image itself before any diagnostic reading takes place. Two such applications are well established internationally and are not represented in the three-task taxonomy above, or in PUI’s five prioritised domains: dose- and scan-time-optimised image reconstruction, and three-dimensional reconstruction and anatomical modelling.

Dose- and scan-time-optimised reconstruction

Deep learning reconstruction (DLR) is arguably the most commercially mature and clinically deployed computer vision application in radiology, used to reduce CT radiation dose or shorten CT/MRI acquisition time while preserving or improving diagnostic image quality, and is now embedded as standard reconstruction software in scanners from every major vendor [23]. Clinical validation in exactly the domains PUI has prioritised is substantial: a stroke-imaging-protocol study found deep learning reconstruction reduced cardiac CT angiography radiation dose while improving image quality relative to iterative reconstruction [16], and a 2025 neuroradiology study found deep-learning-accelerated MRI halved scan time across routine brain examinations while preserving diagnostic image quality [24]. Because this technology operates at the scanner/reconstruction level rather than as a downstream reporting-workflow integration, it sits outside the orchestration-layer architecture PUI has been procured around [8,10]; based on

available procurement documentation, PUI does not extend into the reconstruction stage itself, even though two of its five domains – brain CT/MRI and chest CT – are exactly the modalities where dose- and scan-time-optimised reconstruction is most mature and widely deployed internationally. Whether this reflects a genuine hardware/software adoption gap in Polish CT and MRI fleets, or simply a governance choice to scope PUI around interpretation rather than acquisition, is not established by the sources reviewed here.

Three-dimensional reconstruction and anatomical modelling

A second reconstruction-stage application converts segmented CT or MRI data into a three-dimensional mesh or volumetric model of an anatomical structure. This has a real, if secondary, diagnostic role: a 2025 study developed a deep-learning pipeline that generated three-dimensional heart models directly from CT and cardiac MRI in congenital heart disease, reporting that clinicians rated the resulting models useful for both diagnostic support and preoperative planning [25]. The wider literature on this application, however, is weighted more heavily toward surgical and procedural planning than toward diagnosis itself: a review of deep learning across CT reconstruction, bone segmentation, and surgical planning in maxillofacial surgery found the majority of published work targets the design of patient-specific implants and surgical guides rather than diagnostic characterisation [26]. This is the main reason three-dimensional reconstruction and anatomical modelling is not treated as a fourth core interpretation task alongside detection, classification, and segmentation in this review: its predominant clinical use case is procedural rather than diagnostic, even though a diagnostic contribution clearly exists. None of PUI's five domains explicitly specify three-dimensional reconstruction as an output, though the neurovascular and skeletal trauma domains are exactly the modality categories – CT angiography, complex fracture imaging – where three-dimensional reconstruction is already routine radiologist practice, typically performed on vendor workstation software rather than as an AI-automated pipeline; the procurement documentation reviewed here does not specify whether PUI's tendered models include this capability.

These two reconstruction-stage applications are therefore best understood as adjacent to, rather than substitutes for, the three interpretation tasks that structure the rest of this review: they change what image the radiologist sees, rather than what a model concludes about it. But because dose- and scan-time-optimised reconstruction is already in mature, widely deployed clinical use in the imaging modalities PUI has prioritised, and three-dimensional reconstruction retains a genuine, if secondary, diagnostic role, both represent relevant comparators for assessing the completeness of any national computer vision programme in radiology, including PUI.

Emerging architectures: vision transformers and foundation models

Beyond convolutional architectures, vision transformers (ViTs) and, more recently, foundation models pretrained on large, often multi-institutional imaging corpora have emerged as a distinct architectural direction in medical image analysis, with reported strengths in capturing long-range spatial dependencies and in transferring across tasks with limited task-specific labelled data [27]. Radiology-focused foundation models – spanning chest radiography, cross-sectional CT, and brain MRI – have predominantly relied on transformer backbones combined with self-supervised pretraining strategies such as masked image modelling and contrastive learning [28], and vision-language foundation models that jointly align imaging and report text are being explored for applications including automated report generation [29,30]. However, as of the evidence and deployments reviewed here, these approaches remain concentrated at the pre-clinical and validation stage: cross-centre, cross-scanner, and cross-population generalisation is inconsistently reported, and few, if any, ViT- or foundation-model-based products have reached CE-certified clinical deployment in Poland or elsewhere at the scale of the CNN-based tools discussed above [28]. This is therefore treated as an emerging direction rather than a mature component of the current Polish implementation landscape, and noted as a priority for future review as clinical-grade evidence accumulates. Despite this absence of clinical deployment, Polish groups are active at the research stage: a Silesian University of Technology team, with the Systems Research Institute of the Polish Academy of Sciences, has published a transformer-based semantic segmentation network for medical imaging [31], the Sano Centre for Computational Medicine and AGH University of Kraków have demonstrated diffusion-based synthetic data generation for training models on endoscopic (surgical-video) images – not radiological images – which illustrates a generative-data capability that could in principle be transferable to radiology [32], and new national compute infrastructure – the €70-million Gaia AI Factory, coordinated by AGH’s Cyfronet centre and listing imaging diagnostics in healthcare among its planned use cases – was inaugurated in May 2026 to support this kind of large-scale model training [33,34,35].

Diagnostic performance and the validation gap

For a radiologist deciding how much weight to place on an AI output, the distinction between technical validity, clinical validity, and clinical utility matters more than a single reported accuracy figure [6]. Technical validity asks whether the algorithm performs consistently on data resembling its training distribution. Clinical validity asks whether that performance holds on the actual patient population, scanner types, and acquisition protocols of a given department – external validation, ideally on multinational, multivendor data, is the standard evidence for this, and it remains

comparatively rare [5,6]. Clinical utility, the least-studied level, asks whether using the tool changes what the radiologist does, how quickly, and with what effect on patient outcomes.

This three-level distinction explains a pattern radiologists increasingly report anecdotally and that the literature is beginning to document more formally: an algorithm with excellent published sensitivity and specificity can still under-perform, over-flag, or simply go unused once deployed in a real department, because the case-mix, scanner hardware, or reporting workflow differs from the validation setting [5,6]. It also underlies the regulatory push, discussed in Section: Governance and regulatory considerations, toward mandatory post-market surveillance of AI medical devices rather than one-off pre-market validation [36].

The Polish implementation landscape

The Platforma Usług Inteligentnych (PUI)

The most consequential recent development for computer vision in Polish radiology is not a single study but a national infrastructure project. Centrum e-Zdrowia, the state agency responsible for Poland's digital health systems, is building the Platforma Usług Inteligentnych (PUI) as part of the "e-Zdrowie KPO" programme, financed through the EU's Krajowy Plan Odbudowy i Zwiększania Odporności (National Recovery and Resilience Plan) [7,8,9]. On the recommendation of the National Consultant in Radiology and Diagnostic Imaging, the platform's first phase concentrates on five diagnostic domains (Table I): detection of lung cancer on chest CT, detection of chest pathology on chest radiographs, detection of breast cancer on mammography, detection of ischaemic and haemorrhagic changes on brain CT/MRI, and detection of traumatic skeletal changes on conventional radiographs [7,9]. CeZ has structured procurement around these same five areas, tendering separately for AI models covering chest CT pathology, brain ischaemia/haemorrhage, skeletal trauma, breast cancer on mammography, and chest radiograph pathology, together with an integration and orchestration layer that will connect certified third-party AI models directly to radiologists' reporting workflow [8,10]. According to CeZ's integration documentation, the hospital's own domain system submits an analysis order to PUI over a REST API, including the imaging data (for example in DICOM format) and a code identifying the requested AI model; PUI queues and prioritises the order, routes it to the selected model and makes the result available for download through the same interface [37]. CeZ does not specify which hospital system initiates the request, but access is described as integration with existing radiology information system (RIS) and picture archiving and communication system (PACS)-class systems [38]; vendor- and product-level integration details were not identified in the sources

reviewed here. Deployment was tied to the KPO funding timeline, with a fixed 30 June 2026 deadline for the programme [7,8,9,10]. On the public sources available, procurement had progressed but was not complete by that date. The main PUI tender was announced on 31 October 2025; the most advantageous offer was selected on 26 February 2026; following an appeal and re-evaluation, the National Appeals Chamber (KIO) dismissed in full the challenge lodged by the second-ranked consortium, as reported on 3 June 2026 [39]. For the AI models, offers had been submitted in all five thematic areas by March 2026, with a contractor selected in one area and the others at the final stage [40]; the contract for the mammography models (a consortium led by Synektik with Carebot) was signed in August 2026, with delivery due by 20 September 2026 [41]. By 21 August 2026, trade press reported that vendors had been selected in all five model areas, with the mammography contract signed that day [41,42]. Free access was planned for 585 of 896 hospitals in the basic hospital security network [43]. By September 2026, individual hospitals reported installing the PUI integration components but described connection and clinical use as planned or in preparation [44,45]. In an interview published on 8 October 2026, the CeZ director stated that PUI would be launched in October 2026, that the first phase would cover the 362 entities that received KPO funding for these services, and that the models would be introduced sequentially – skeletal (bone) first, then brain ischaemia, with chest radiograph, chest CT and mammography to follow [46]. As of 19 October 2026 the author did not identify a public announcement confirming that routine production use had begun; the programme status described here is therefore accurate only as of that date.

Framed explicitly around the radiologist rather than the technologist, CeZ's own description of the platform's purpose is to let radiologists "use modern, certified AI models" to "analyse diagnostic images faster and more precisely, detect subtle pathological changes, and more efficiently prioritise cases requiring urgent intervention" such as stroke, while reducing time spent on the administrative components of reporting (all CeZ statements quoted in this paragraph are the author's translation from the Polish original) [9]. This is framed as a workforce intervention as much as a diagnostic one: CeZ cites data from the Naczelna Izba Lekarska (Polish Supreme Medical Chamber) that Poland has fewer than 4,600 practising radiologists nationally, equivalent to roughly 123 per million population – just below the EU-wide average of 127 per million reported across 27 member states – indicating that Poland's radiologist workforce pressure, while real, reflects overall physician-workforce and geographic/subspecialty distribution pressures rather than Poland being a per-capita outlier within the EU, and positions AI-assisted triage and reporting support as a direct response to that pressure [9,47]. Poland is also among nine EU Member States expected to lose a higher share of their radiologist workforce to retirement within five years than

the EU average of 19% [47]; regional-distribution data specific to Polish radiologists were not identified in the sources reviewed here and would be needed to characterise this pressure more precisely. The programme’s phased timeline, from the 2024 adoption baseline through to the fixed 2026 funding deadline, is summarised in Figure 2.

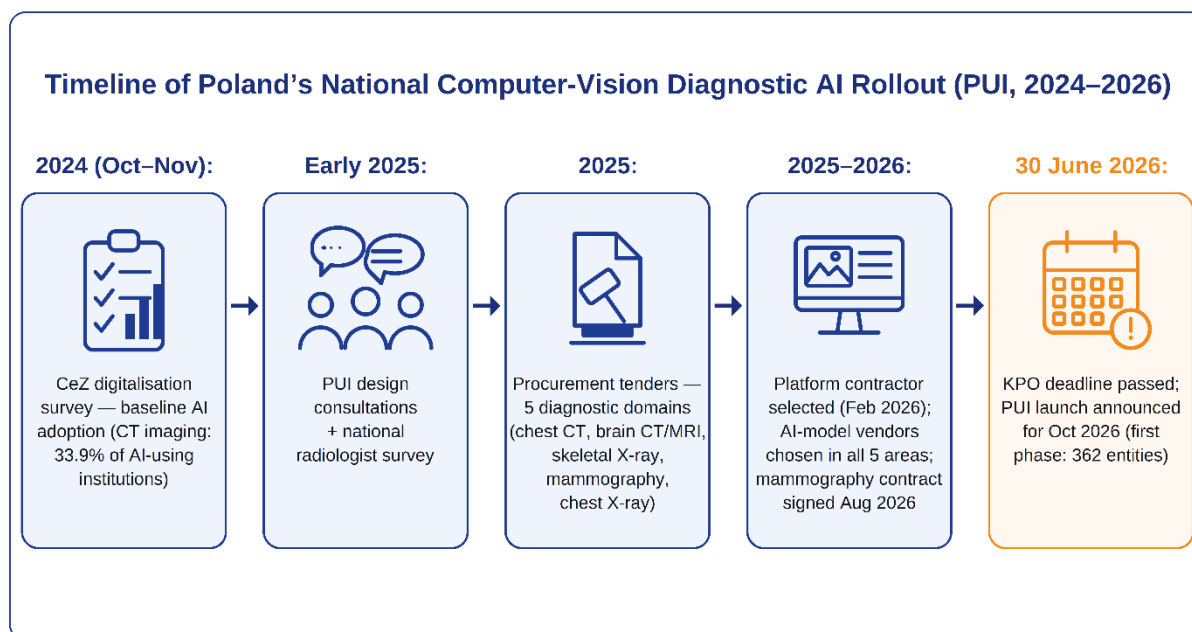


Figure 2. Timeline of Poland’s national computer-vision diagnostic AI rollout (Platforma Usług Inteligentnych, PUI) from baseline adoption survey to the KPO-funded 2026 deployment deadline. Programme status is shown as of 19 October 2026.

Radiologists’ current experience and attitudes

Ahead of finalising PUI’s design, CeZ ran a national consultation and survey process specifically targeting radiologists’ existing experience of, and attitudes toward, AI in their daily reporting practice, alongside workshops involving representatives of medical chambers, hospitals, e-health experts, and technology vendors [11,48]. This complements the procurement-oriented and general-adoption studies that have so far represented Poland in the international literature, adding a radiologist-specific, prospective perspective directly tied to a live national deployment. Together with a mixed-methods analysis of psychographic barriers among Polish healthcare professionals and an assessment of the gap between the clinical promise and the operational reality of AI use cases in Polish hospitals, this body of evidence indicates that clinician scepticism, workflow disruption, and unclear liability remain barriers relevant to the technical rollout [49,50]. As of 19 October 2026, CeZ’s own survey has been described publicly only through participation calls and methodology summaries; no quantitative topline results have yet appeared in a peer-reviewed or publicly accessible report, so it is treated here as a named, ongoing evidence source rather than a set of findings to be summarised [11,48].

Adoption to date

CeZ's eighth national survey of healthcare digitalisation (conducted October-November 2024 across close to 11,200 institutions) provides the first quantified picture of where AI is already used in Polish medical imaging, ahead of PUI's own rollout: among institutions already using AI-supported tools, imaging-related applications are concentrated in CT (33.9% of AI-using institutions, which represented 4.7% of the 11,185 respondents), with smaller shares in other modalities [51]. This baseline is useful as a pre-rollout reference point against which the impact of PUI can be measured in future surveys, and it underscores how much of the diagnostic AI adoption curve in Poland is still ahead of it, concentrated in the PUI rollout rather than organic single-vendor purchases.

Individual hospitals have moved earlier and independently. A frequently cited early case is the Joannitas Hospital in Pszczyna (Silesian Voivodeship), which reported in 2024 that it had implemented an AI system to support its radiologists' reporting workflow, described locally as helping radiologists analyse imaging studies more quickly [52]. Cases of this kind remain sparsely documented in the peer-reviewed literature to date, appearing mainly as institutional press releases and trade press rather than published evaluation studies. Poland's e-health press has also tracked international product milestones relevant to the chest radiograph domain PUI has itself prioritised: the CE certification of ChestLink (Oxipit, a Lithuanian developer), the first fully autonomous chest X-ray AI system authorised to filter and report normal studies without radiologist review, was covered as a landmark development in this domain, even though the product itself is not Polish-developed and represents a materially different regulatory and clinical-risk paradigm – autonomous, no-human-in-the-loop triage – from the concurrent-reader model that PUI's own chest radiograph tools are designed around [53].

Table I. PUI diagnostic domains mapped to modality, target pathology, and international evidence status (evidence-status entries are the author’s qualitative synthesis of the cited sources)

Diagnostic domain (PUI)	Modality	Target pathology	International evidence status
Chest CT oncology	CT	Lung cancer detection	Extensive detection/classification evidence; chest imaging has the most products with higher-level evidence, but multicentre and multinational validation remains limited overall [5,14,19]
Chest radiograph pathology	Radiograph (X-ray)	Chest pathology (illustrative examples: pneumonia, pneumothorax, nodules)	Chest imaging is among the best-evidenced CE-marked areas [5]; a CE-marked autonomous chest X-ray product exists [53]
Breast oncology	Mammography	Breast cancer detection	Extensive evidence; large screening trials of AI-supported mammography reading now published (MASAI, PRAIM) [5,54,55]
Neurovascular	Brain CT / MRI	Ischaemic and haemorrhagic stroke detection	Neuroimaging overall has the largest number of CE-marked products, but most lack evidence or have only lower-level evidence (not stroke-specific); stroke triage/large-vessel-occlusion evidence and real-world workflow data growing [5,14]
Musculoskeletal trauma	Radiograph (X-ray)	Fracture detection	Strong technical/diagnostic-accuracy evidence; fewer outcome-level studies [4,14]

Governance and regulatory considerations

Diagnostic AI used to interpret radiological images already falls within scope of the EU Medical Device Regulation, and will additionally become subject to the EU AI Act’s high-risk system requirements (Regulation (EU) 2024/1689 [56], as amended by the Digital Omnibus on AI, Regulation (EU) 2026/1744 [57]) once these apply to regulated medical devices, since diagnostic support tools in radiology meet the Act’s Annex I/Article 6(1) criteria for high-risk medical AI [36]. This medical-device pathway does not yet apply: under the Digital Omnibus on AI, which entered into force on 27 July 2026 [57], the high-risk obligations for AI systems that are safety components

of, or are themselves, products covered by Annex I sectoral legislation such as the MDR apply from 2 August 2028, and those for stand-alone Annex III systems from 2 December 2027 (the original text of the Act provided for 2 August 2027 and 2 August 2026, respectively [56]). In practice, PUI's 2026 rollout will therefore operate under existing MDR obligations for roughly two years before the AI Act's medical-device-specific high-risk requirements formally engage on 2 August 2028 – a distinction relevant to when, rather than whether, the accountability and monitoring questions below become statutory rather than advisory. The European Society of Radiology has published consensus recommendations on both post-market surveillance of AI medical devices and on practical implementation of the AI Act's requirements specifically for radiology departments, emphasising continuous performance monitoring after deployment rather than reliance on pre-market CE certification alone [36,58]. For a radiologist, this has a direct practical implication distinct from the acquisition-phase governance questions that dominated earlier reviews of AI in radiology: the question is not primarily who configures or maintains the tool, but who remains accountable for a missed or incorrect finding when an AI system was used as part of the interpretation, how that AI output is documented in the report, and what post-deployment monitoring obligations fall on the reporting radiologist and the department as a “deployer” under the AI Act. As Poland's PUI programme moves from procurement to live clinical use from late 2026, and toward the AI Act's medical-device compliance deadline in August 2028, these accountability and monitoring questions – rather than the underlying model performance, which is already reasonably documented internationally – are likely to be the practical bottleneck for radiologists' day-to-day use of the platform [36,50,58].

DISCUSSION

Three points follow from placing Poland's radiologist-facing computer vision rollout against the international diagnostic-performance literature.

First, the international evidence base on detection, classification, and segmentation performance is now mature enough that Poland's PUI programme is not entering a technical vacuum: chest, neuro, and breast imaging AI – domains that largely overlap with PUI's five prioritised domains – are among the best-validated application areas globally [5,13]. The technology risk therefore appears smaller than the implementation-evidence gap highlighted throughout this review. What the literature consistently identifies as under-evidenced – clinical utility, workflow effect, and outcome impact after deployment – is exactly what a nationally coordinated, five-domain rollout with a fixed funding deadline is well positioned to generate, representing a valuable opportunity

for Polish radiology departments and professional bodies to contribute real-world evidence to this international gap.

Second, Poland's radiologist workforce pressure gives its AI adoption a different primary justification than in many higher-resourced systems: triage and reporting-support functions that reduce time-to-report for urgent findings such as stroke are framed by CeZ explicitly as a workforce response, not solely a diagnostic-accuracy improvement [9,18]. This reframes the relevant outcome measure for Polish evaluation studies going forward – away from sensitivity/specificity alone, and toward time-to-report, worklist prioritisation accuracy, and radiologist workload, which are exactly the “level 3–5” outcomes the international literature says are missing everywhere [4,5].

Third, the barriers already documented in Polish healthcare AI adoption more broadly – scepticism among clinicians, unclear liability, and gaps between procurement ambition and operational reality [49,50] – point to radiologist trust, training, and accountability as factors likely to be as relevant to PUI's uptake as the underlying model performance itself. The CeZ radiologist survey described in Section: Radiologists' current experience and attitudes remains the most direct source of this kind of evidence for Poland specifically, and its publication would represent a concrete opportunity for Polish authors to contribute to the international literature on real-world AI implementation [11,48].

Limitations

This is a narrative, not a systematic, review, and its Polish-context evidence base draws substantially on institutional and grey-literature sources (Centrum e-Zdrowia communications, hospital press releases) rather than peer-reviewed studies, reflecting the genuine scarcity of published Polish evidence on diagnostic AI performance and adoption at the time of writing. Several sources describing PUI's scope and timeline are procurement and policy communications rather than academic publications and may change as the programme progresses; readers should treat programme details as accurate as of 19 October 2026 (the information cut-off date) rather than fixed. The international diagnostic-performance literature synthesised in Sections: Computer vision across diagnostic tasks and Diagnostic performance and the validation gap is itself skewed toward high-resource health systems, which limits direct generalisability of reported accuracy figures to the Polish case-mix and equipment base. The scope of this review follows PUI's first-phase diagnostic domains – chest CT, chest radiograph, mammography, brain CT/MRI, and skeletal radiograph – and therefore does not cover ultrasound, a modality with its own substantial and

growing computer vision literature (e.g. in obstetrics, cardiology, and point-of-care applications) that falls outside PUI's current scope and outside the scope of this review.

CONCLUSIONS

Computer vision for diagnostic image interpretation – detection, classification/triage, and segmentation/quantification – is now supported by a substantial and maturing international evidence base, concentrated in domains (chest, neuro, breast imaging) that largely overlap with those that Poland's national Platforma Usług Inteligentnych programme has chosen to prioritise. What is missing is not proof that these algorithms can work, but evidence of how they perform once deployed at national scale inside a specific, resource-constrained health system. Poland's PUI rollout, driven by radiologist workforce pressure (rising workload and uneven distribution rather than a per-capita deficit) and a fixed EU funding deadline, is a live natural experiment in exactly the "validation gap" the international literature describes, and represents a substantial opportunity for original Polish research. Closing that gap is both a scientific opportunity and, given the workforce pressures described here, a practical necessity for Polish radiology over the next several years.

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Conflict of interest

The author declares no conflict of interest.

Use of AI tools statement

GPT-6 was used for image generation of Figure 2.

Authors' contribution

Study design – P. Malik

Data collection – P. Malik

Manuscript preparation – P. Malik

Literature research – P. Malik

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