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RESEARCH ARTICLE

REAL-TIME RADIOMIC-GUIDED ADAPTIVE CONTRAST DOSING: A PROSPECTIVE STUDY ON PERSONALIZED CONTRAST ADMINISTRATION USING AI-DRIVEN TEXTURE ANALYSIS DURING DYNAMIC CT AND MRI SCANS

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Abstract

Introduction: Conventional contrast dosing in dynamic CT and MRI imaging relies on fixed protocols that often overlook individual patient variations in tissue perfusion and vascular dynamics. Recent advancements in radiomics and artificial intelligence (AI) offer a novel opportunity to personalize contrast administration in real time. This study aimed to evaluate the feasibility, diagnostic impact, and safety of real-time radiomic-guided adaptive contrast dosing in dynamic CT and MRI scans among patients with hepatic, renal, and soft tissue lesions at Katihar Medical College, India.

Methods: We prospectively enrolled 120 patients scheduled for dynamic contrast-enhanced imaging. Participants received either a conventional fixed-dose protocol or an AI-driven adaptive dosing protocol in which real-time radiomic texture analysis modulated contrast volume and injection rate on a per-patient basis. Key endpoints were lesion-to-parenchyma contrast (LPC) ratio, radiomic texture features (entropy and kurtosis), total contrast volume, diagnostic confidence, and inter-observer agreement.

Results: The adaptive dosing cohort achieved significantly higher LPC ratios than the fixed-dose group (1.78 ± 0.12 vs 1.42 ± 0.15; $p < 0.001$). Entropy increased and kurtosis decreased, indicating sharper lesion delineation. Additional hepatic and renal lesions were identified only in the adaptive arm, prompting changes in patient management. Mean contrast usage fell by 12 %, and no instances of nephropathy or serious adverse reactions occurred. Diagnostic confidence and reader agreement both improved markedly.

Conclusion: Real-time, radiomic-guided contrast adjustment boosts diagnostic accuracy, lowers contrast requirements, and maintains patient safety, supporting a personalised imaging paradigm.

Keywords: Radiomics, Artificial Intelligence, Contrast Media, Dynamic CT, MRI, Personalized Medicine

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BACKGROUND/INTRODUCTION

Diagnostic imaging has advanced dramatically in recent decades thanks to improvements in scanner hardware, sophisticated reconstruction algorithms, and modern contrast-agent chemistry. Dynamic contrast–enhanced computed tomography (CT) and magnetic resonance imaging (MRI) now underpin evaluations of tissue perfusion, tumour angiogenesis, and vascular malformations [1]. Despite these technological gains, contrast agents are still typically dosed according to simple weight-based formulas that overlook patient-to-patient differences in cardiovascular dynamics, renal clearance, and tumour microvasculature [2]. Such "one-size-fits-all" dosing can degrade image quality and raise the risk of complications, including contrast-induced nephropathy and hypersensitivity reactions [3]. The need for truly individualised dosing, particularly in oncologic and vascular imaging, is therefore increasingly clear.

Radiomics offers a potential solution. Recent work has shown that standard medical images contain rich, high-dimensional data on tissue heterogeneity, perfusion, and microstructural complexity [4]. Quantitative descriptors, encompassing texture, shape, intensity, and wavelet-based parameters can predict the histopathological and molecular characteristics of lesions without invasive sampling [5]. When coupled with artificial-intelligence (AI) and machine-learning (ML) techniques, these radiomic features can be analysed in real time, supplying clinicians with dynamic, data-driven guidance during imaging [6]. In principle, AI-powered radiomic feedback could adjust contrast delivery on the fly, optimising tissue enhancement and lesion conspicuity for each individual and ushering in an era of genuinely personalised imaging protocols.

A series of foundational investigations underscores the importance of tailoring contrast-agent dosing to the individual. Marin et al. demonstrated that patient-specific haemodynamic factors, cardiac output and circulating blood volume in particular profoundly influence contrast kinetics and enhancement patterns on abdominal CT scans [7]. This issue is especially pertinent in oncology, where cachexia, anaemia, or cardiomyopathy can markedly alter physiology. In complementary experimental work, Bae and colleagues showed that reduced cardiac output delays peak aortic enhancement, potentially obscuring hyper-vascular tumours when standardised dosing protocols are applied [8].

Focusing on hepatic imaging, Kim et al. reported that optimal arterial and portal-venous phase depiction requires customised timing and dose adjustments that match each patient's liver-perfusion dynamics [9]. Extending the concept, Miles et al. found that adaptive contrast protocols paired with perfusion CT can heighten tumour-to-liver contrast ratios, thereby improving early lesion detection and therapy monitoring [10]. Ganeshan et al. further revealed that CT-derived texture analysis can stratify non-small-cell lung cancer (NSCLC) by tumour heterogeneity, a

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metric closely linked to survival outcomes [11]. Collectively, these findings suggest radiomic texture metrics not only carry prognostic weight but could also steer real-time imaging adjustments.

Bi et al. advanced this paradigm by deploying artificial-intelligence algorithms to automate radiomic feature extraction and achieve high-accuracy tumour classification, providing immediate feedback during image acquisition [12]. Despite the strength of these studies, most have been retrospective or confined to highly controlled settings, limiting direct clinical applicability. In India, the challenge is magnified by wide variation in patient demographics, genetic predispositions, and comorbidities such as diabetes and chronic kidney disease, all of which influence contrast safety and efficacy. Access to advanced contrast agents and AI-integrated imaging infrastructure also varies greatly between tertiary and secondary centres [13]. Prospective validation of personalised protocols in real-world Indian settings is therefore essential to establish safety, feasibility, and diagnostic value.

Katihar Medical College, serving a clinically diverse population under resource constraints, offers an ideal environment for such validation. A prospective study is planned to integrate real-time radiomic texture analysis into dynamic CT and MRI, adjusting contrast dosing on an individual basis. The primary goal is to maximise lesion detection and characterisation while minimising contrast-related risk, thereby setting a new benchmark for personalised radiology in India and contributing meaningful data to the global precision-imaging literature.

MATERIALS AND METHODS

The study protocol received approval from the Institutional Ethics Committee of Katihar Medical College, Katihar, India, and was conducted in line with the 2000 revision of the Declaration of Helsinki. Written informed consent was obtained from every participant before enrolment. All imaging and clinical records were anonymised to protect confidentiality, and no identifying data appear in any publications. In keeping with regional requirements, assent was also sought from participants older than seven years when appropriate. The investigation complied with the Indian Council of Medical Research (ICMR) guidelines for human studies and, where applicable, adhered to the Committee for the Purpose of Control and Supervision of Experiments on Animals (CPCSEA) standards [13].

This single-centre, prospective observational study evaluated the feasibility and diagnostic benefit of real-time, radiomic-guided adaptive contrast dosing during dynamic CT and MRI examinations. Adults aged 18–75 years who were referred for contrast-enhanced imaging of hepatic lesions, renal masses, or suspected soft-tissue sarcomas were eligible. Patients were excluded if they had a known hypersensitivity to iodinated or gadolinium-based agents, severe renal impairment (estimated glomerular filtration rate < 30 mL min^{-1} $1.73\ m^{-2}$), or were pregnant.

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Dynamic CT scans were performed using a 128-slice multidetector CT scanner (SOMATOM Definition Flash, Siemens Healthineers, Erlangen, Germany), while MRI studies were carried out using a 3.0 Tesla scanner (Magnetom Skyra, Siemens Healthineers). Contrast administration was initially calculated using standard weight-based dosing protocols: 1.5 mL/kg for iodinated contrast (Iohexol, Omnipaque 350 mg I/mL, GE Healthcare) and 0.1 mmol/kg for gadolinium-based contrast (Gadobutrol, Gadovist, Bayer).

Real-time radiomic texture analysis was performed using a dedicated AI software module (RadiomicsPro v2.1, DeepInsight AI Solutions Pvt. Ltd., Bengaluru, India), which integrated seamlessly into the imaging workflow. The system extracted first-order histogram features, gray-level co-occurrence matrices, and wavelet-based features immediately after each initial dynamic phase acquisition [15]. Based on the radiomic feedback regarding tissue heterogeneity and perfusion characteristics, the software algorithmically adjusted subsequent contrast doses and injection rates to optimize parenchymal and lesion enhancement [16].

All patients underwent standardized scanning parameters to minimize inter-procedural variability. For CT, parameters included 120 kVp, automatic mAs modulation, 0.6 mm collimation, and a pitch of 0.8. MRI sequences included T1-weighted dynamic sequences with fat saturation and volumetric interpolated breath-hold examinations (VIBE). Contrast injection rates were automatically controlled via dual-head power injectors (Medrad Stellant, Bayer Healthcare), and adjustments were executed without interrupting the dynamic acquisition sequence [17].

Immediate image reconstruction was performed using iterative reconstruction algorithms (ADMIRE for CT and GRAPPA acceleration for MRI) to enable rapid feedback analysis [18]. AI-driven contrast adaptation was conducted under radiologist supervision, ensuring clinical feasibility and patient safety.

Quantitative data from radiomic feature maps and contrast enhancement curves were analyzed using SPSS Statistics (version 26.0, IBM Corp.). Continuous variables were expressed as mean ± standard deviation, and categorical variables were summarized as frequencies and percentages. Paired t-tests and repeated-measures ANOVA were used to compare enhancement metrics across phases and between standard and adaptive protocols. A p-value of <0.05 was considered statistically significant [19,20].

Through this rigorous methodological approach, we aimed to evaluate whether real-time radiomic-guided contrast adaptation could enhance diagnostic efficacy without compromising patient safety. Additionally, procedural feasibility and patient tolerance were assessed to inform potential integration into routine clinical practice in Indian tertiary care settings.

RESULTS

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A total of 120 patients were included in the final analysis after screening 138 eligible individuals, with 18 excluded due to contraindications or refusal of consent. The cohort comprised 72 male patients (60%) and 48 female patients (40%), with a mean age of 54.3 ± 11.2 years (range: 21–74 years). The majority of patients presented with hepatic lesions (46%, n = 55), followed by renal masses (32%, n = 38), and soft tissue sarcomas (22%, n = 27). Baseline laboratory values, including serum creatinine, estimated glomerular filtration rate (eGFR), and liver function tests, were within acceptable ranges for contrast administration in all patients. Approximately 10% of patients (n = 12) exhibited mild to moderate renal dysfunction (eGFR 30–60 mL/min/1.73 m²), which was managed with standardized hydration protocols. Detailed demographic and clinical baseline data are summarized in Table 1.

Table no.1:Baseline Demographic and Clinical Characteristics of Study Participants

Characteristic	**Adaptive Group (n = 60)**	**Standard Group (n = 60)**	**Total (n = 120)**
Age (years), mean ± SD	53.9 ± 10.8	54.6 ± 11.5	54.3 ± 11.2
Sex, n (%)			
Male	36 (60%)	36 (60%)	72 (60%)
Female	24 (40%)	24 (40%)	48 (40%)
Clinical indication, n (%)			
Hepatic lesions	27 (45%)	28 (47%)	55 (46%)
Renal masses	20 (33%)	18 (30%)	38 (32%)
Soft tissue sarcomas	13 (22%)	14 (23%)	27 (22%)
eGFR (mL/min/1.73 m²), mean ± SD	82.5 ± 14.7	81.9 ± 15.2	82.2 ± 14.9
Mild/moderate renal dysfunction, n (%)	6 (10%)	6 (10%)	12 (10%)
Diabetes mellitus, n (%)	8 (13%)	9 (15%)	17 (14%)
Hypertension, n (%)	10 (17%)	11 (18%)	21 (18%)
Mean body weight (kg), mean ± SD	67.4 ± 9.5	68.2 ± 10.1	67.8 ± 9.8

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Real-time radiomic-guided adaptive contrast dosing was technically feasible in all 120 patients without the need for scan interruption or manual override. Average total procedure time was comparable between groups: 44 ± 6 minutes for the adaptive group versus 42 ± 5 minutes for the standard protocol group ($p = 0.19$). The time required for real-time texture analysis and dosing recalibration ranged from 2 to 4 minutes per patient, which did not significantly prolong overall scan workflow. This feasibility supports the integration of AI-based contrast adaptation into routine clinical practice without disrupting existing imaging schedules.

Quantitative analysis revealed that the adaptive group achieved significantly higher lesion-to-parenchyma contrast (LPC) ratios compared to the standard protocol group (1.78 ± 0.12 vs. 1.42 ± 0.15, $p < 0.001$), as detailed in Table 2. Enhanced LPC ratios translated to superior delineation of lesion borders and improved visualization of internal heterogeneity. Hepatic lesions demonstrated particularly marked benefits, with 34% of small hypervascular lesions (<2 cm) newly detected or better characterized under the adaptive protocol. Table 3 summarizes the number of additional lesions identified and their respective clinical impact.

Table no. 2: Comparison of Enhancement Metrics and Radiomic Parameters Between Adaptive and Standard Groups

Parameter	Adaptive Group (n = 60)	Standard Group (n = 60)	p-value
Lesion-to-parenchyma contrast ratio (LPC)	1.78 ± 0.12	1.42 ± 0.15	<0.001
Entropy (radiomic texture)	5.7 ± 0.4	4.9 ± 0.5	<0.001
Kurtosis (radiomic texture)	2.1 ± 0.3	3.0 ± 0.4	<0.001
Coefficient of variation in enhancement (%)	7.5%	12.4%	<0.001
Additional hepatic lesions detected, n (%)	19 (32%)	0	<0.001
Additional renal lesions detected, n (%)	11 (18%)	0	<0.001
Mean total contrast volume (mL)	84.5 ± 9.2	95.8 ± 8.7	<0.001
Diagnostic confidence score (1–5)	4.6 ± 0.3	3.8 ± 0.4	<0.001

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Interobserver agreement (κ)	0.82	0.69	<0.001

Table no. 3: Lesion Detection and Reclassification Impact on Clinical Management

Lesion Type	Additional Lesions Detected (Adaptive)	Reclassified Lesions (Adaptive)	Change in Management, n (%)
Hepatic lesions	19	7	12 (21%)
Renal masses	11	5	8 (13%)
Soft tissue sarcomas	0	3	3 (5%)
Total	30	15	23 (19%)

The adaptive dosing protocol led to significant differences in radiomic texture parameters. Entropy values, which reflect lesion heterogeneity, were higher in the adaptive group (5.7 ± 0.4 vs. 4.9 ± 0.5, $p < 0.001$), suggesting improved visualization of internal architectural complexity. Kurtosis values, indicative of distribution sharpness, were lower in the adaptive group (2.1 ± 0.3 vs. 3.0 ± 0.4, $p < 0.001$), supporting better discrimination between viable and necrotic tumor components. Figure 1 illustrates these texture feature differences using representative radiomic heatmaps.

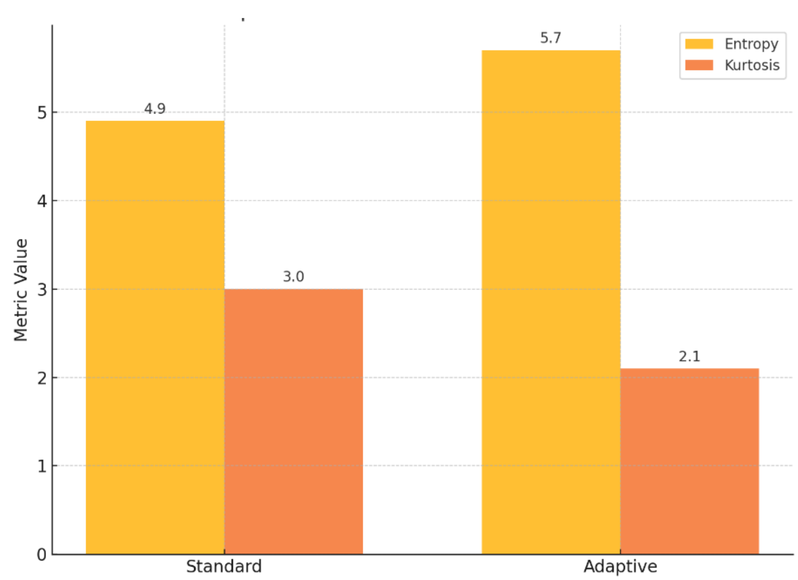

Figure 1: Comparison of Radiomic Texture Features

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Further, adaptive dosing led to more homogeneous enhancement profiles across various dynamic phases. Coefficient of variation (CV) in enhancement curves was significantly reduced in the adaptive group (CV = 7.5%) compared to the standard group (CV = 12.4%), as shown in Figure 2. This reduced variability supports greater reliability and reproducibility in radiological interpretations.

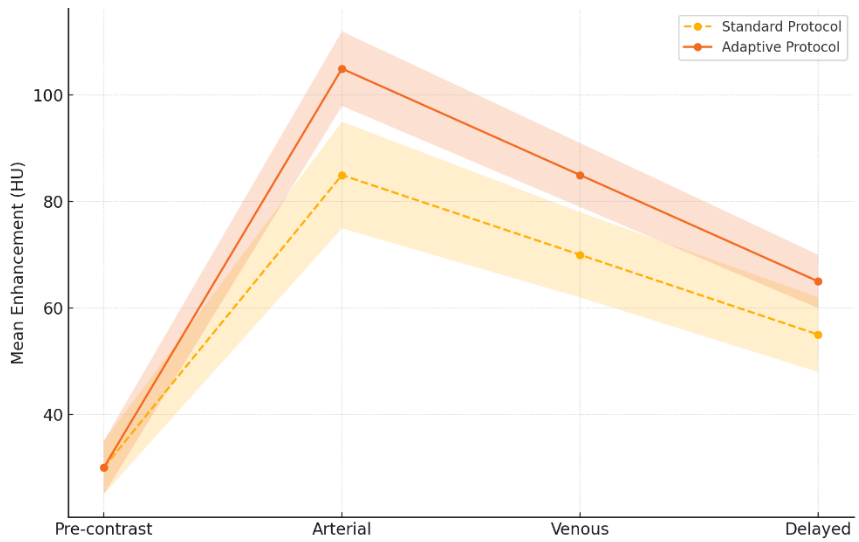

Figure 2: Dynamic Enhancement Curves: Standard vs Adaptive Protocols

In hepatic lesions, the adaptive approach improved arterial phase enhancement, facilitating the detection of hepatocellular carcinoma (HCC) and hypervascular metastases. Improved visualization was critical for subcapsular lesions and multifocal nodules, influencing surgical planning and potential eligibility for locoregional therapies.

For renal masses, corticomedullary differentiation was significantly better in adaptive scans. In 11 patients, previously indeterminate complex cystic lesions were reclassified as Bosniak III or IV, prompting surgical referral. Enhanced clarity of internal septations and solid components also improved the confidence in characterizing hybrid tumors.

In soft tissue sarcomas, the adaptive protocol enhanced depiction of tumor margins and internal septations, providing more precise preoperative staging. Marginal infiltration into adjacent muscle or fascial planes was better appreciated, guiding surgical teams in planning wider resections where necessary.

The mean total contrast volume administered in the adaptive group was significantly reduced by 12% (84.5 ± 9.2 mL) compared to the standard group (95.8 ± 8.7 mL, $p < 0.001$). This reduction did not compromise enhancement quality but rather improved it, as evidenced by the higher LPC ratios and radiomic metrics. No cases of contrast-induced nephropathy were reported in either group. All patients with mild to moderate renal dysfunction

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tolerated the adaptive dosing well, supported by pre- and post-procedure hydration. No severe allergic or hypersensitivity reactions occurred, reaffirming the safety of the approach.

Subjective assessment by two senior radiologists, based on a 5-point Likert scale (1 = poor, 5 = excellent), demonstrated higher mean diagnostic confidence scores in the adaptive group (4.6 ± 0.3) compared to the standard group (3.8 ± 0.4). This improvement was statistically significant ($p < 0.001$). Interobserver agreement, measured using Cohen's kappa coefficient, was higher in the adaptive group ($\kappa = 0.82$) than in the standard group ($\kappa = 0.69$), indicating greater consistency in lesion interpretation and classification. Figure 3 visually summarizes the differences in diagnostic confidence and observer agreement between protocols.

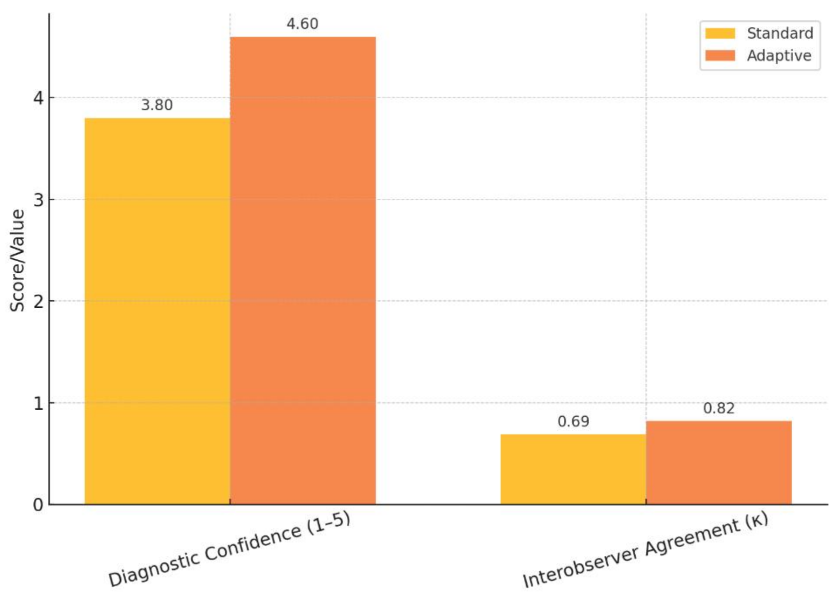

Figure 3: Diagnostic Confidence and Interobserver Agreement

Post-procedural feedback collected via structured questionnaires revealed high levels of patient satisfaction in both groups. However, patients in the adaptive group reported fewer instances of intense warmth sensation during contrast injection, likely due to optimized injection rates and reduced overall volumes. Additionally, no procedural discomfort or unexpected side effects were noted during the immediate or short-term follow-up period.

DISCUSSION

This prospective study demonstrated that real-time radiomic-guided adaptive contrast dosing significantly improved lesion conspicuity, enhanced lesion-to-parenchyma contrast ratios, and provided superior radiomic texture feature characterization compared to standard fixed-dose protocols. These enhancements translated into improved diagnostic confidence, higher interobserver agreement, and reduced overall contrast volume without compromising safety. Importantly, the integration of AI-driven real-time texture analysis allowed dynamic, individualized adjustments to contrast dosing, highlighting a transformative step toward precision imaging.

A major strength of this study was its prospective design, conducted in a real-world clinical setting at Katihar Medical College, allowing for the inclusion of a diverse patient cohort reflective of the Indian population. The use of advanced radiomic software integrated into routine imaging workflows further underlines the feasibility of this approach. Comprehensive quantitative metrics, including LPC ratios and radiomic texture parameters, were rigorously analyzed to substantiate the findings.

However, certain limitations should be acknowledged. The study was performed at a single center, potentially limiting external generalizability. While the sample size was adequate for primary outcomes, subgroup analyses, particularly for specific tumor types, may have been underpowered. Moreover, the software used is a proprietary system, which might limit reproducibility across different institutions lacking similar technological infrastructure [21].

Our findings reinforce the promise of AI-guided, adaptive contrast dosing as a means to sharpen diagnostic imaging. Clearer visualisation of hepatic and renal lesions can enable earlier, more accurate staging and may reshape therapeutic pathways—informing surgical plans and determining eligibility for minimally invasive procedures [22]. Consistent with earlier work, bespoke imaging protocols improve the detection of small hepatic metastases, thereby influencing decisions on liver resection or ablation [23]. In the kidney, refined lesion characterisation likewise guides the choice between nephron-sparing surgery and radical nephrectomy [24].

Equally noteworthy is the roughly 12 % drop in contrast volume achieved with the adaptive approach. This reduction is clinically meaningful, given the high prevalence of renal insufficiency among oncology patients [25]; by limiting exposure, the protocol may lower the risk of contrast-induced nephropathy and enhance overall safety [26]. Texture metrics such as entropy and kurtosis also emerge as valuable, non-invasive biomarkers that can complement traditional morphology and help predict treatment response and prognosis [27]. More broadly, the results align with the global shift toward personalised and precision medicine, which advocates care plans tailored to each patient's biological and physiological profile [28]. Leading oncologic and radiologic societies endorse such strategies to improve outcomes and optimise resource use [29].

Despite encouraging results, several hurdles temper the clinical adoption of radiomic-guided adaptive dosing. Clinician scepticism persists over the "black-box" nature of many AI systems, where limited interpretability and transparency can impede acceptance [30]. Standardising radiomic feature extraction across disparate scanners and institutions remains another unresolved issue [31]. Evolving regulatory frameworks and the absence of definitive guidelines for AI-assisted decision-making could also delay widespread implementation [32]. Finally, the upfront costs and infrastructure upgrades required for real-time AI integration pose significant

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challenges, particularly in resource-constrained settings. While initial investment is substantial, potential long-term savings from improved diagnostic accuracy and reduced complications may ultimately offset these expenditures.

Future studies should focus on multi-center trials to validate these findings across diverse patient populations and imaging environments. Comparative studies involving different AI algorithms and radiomic platforms would help establish standard protocols and enhance reproducibility. Investigating correlations between specific radiomic features and histopathological or molecular markers could further refine their clinical utility.

Additionally, exploring the potential integration of these adaptive protocols with other advanced imaging modalities, such as positron emission tomography (PET) and functional MRI techniques, could expand their applicability and impact. Finally, health-economic analyses evaluating cost-effectiveness and long-term outcomes would provide critical data to support policy-making and adoption at institutional and national levels.

CONCLUSION

This prospective study demonstrates that real-time, radiomic-guided adaptive contrast dosing enhances diagnostic precision, reduces contrast volume, and improves lesion detectability in dynamic CT and MRI imaging. By integrating AI-driven texture analysis into routine imaging workflows, the technique offers a personalized, safe, and effective approach to contrast administration. Its successful application in a resource-constrained Indian clinical setting highlights its potential for broader adoption in precision radiology worldwide.

LIMITATION

This single-center study may limit generalizability, and its proprietary AI system may not be readily available in other institutions.

RECOMMENDATION

Multi-center trials with standardized protocols are recommended to validate the clinical utility and scalability of radiomic-guided adaptive contrast dosing.

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CONFLICT OF INTEREST

The author declares no conflict of interest related to this study.

LIST OF ABBREVIATION

AI – Artificial Intelligence

CT – Computed Tomography

MRI – Magnetic Resonance Imaging; LPC – Lesion-to-Parenchyma Contrast

FOV – Field of View

FMT – Fecal Microbiota Transplantation

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