

UDC 004.85:616.711-073.756.8(045)
DOI:10.18372/1990-5548.89.21469

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SPATIAL-RESOLUTION ROBUSTNESS OF CT-BASED VERTEBRAL FRAGILITY SCREENING IN POTENTIALLY WAR-AFFECTED INDIVIDUALS

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Abstract—The paper is devoted to preserving the accuracy of machine-learning models for computed tomography based vertebral fragility screening under degraded image acquisition, typical of mobile and field-deployed scanners in war-affected regions. The paper proposes a paired evaluation protocol, in which a model trained on clean features is applied twice to the same held-out vertebrae, which is based on controlled synthetic degradation of the same computed tomography volumes: additive noise (15, 30, 50 HU), in-plane Gaussian blur ($\sigma = 0.5, 1, 2$ mm) and slice-thickness coarsening (2, 3, 5, 7 mm). The paper develops a comparative assessment of four imaging representations of vertebral bone on two independent cohorts (106 patients, 478 vertebrae and 126 patients, 589 vertebrae), the paired difference of the area under the ROC curve being estimated by a patient-clustered bootstrap. Additive noise produced no dose-consistent effect. In-plane blur reduced the area under the curve of the radiomics representation by 0.096 (95 % CI $-0.165, -0.025$) and 0.112 ($-0.169, -0.053$) in the two cohorts, whereas the mean-attenuation representation stayed within the null interval at every condition (0.732 and 0.665 on clean data). The results of the work can be used to select acquisition-robust imaging biomarkers for opportunistic screening of war-affected and displaced individuals, whose mean age matches that of the cohorts studied and who are scanned wherever equipment is available.

Keywords—Machine learning, computed tomography, image degradation, vertebral fragility, domain shift, radiomics, potentially war-affected populations, opportunistic screening.

I. INTRODUCTION

A machine-learning model for opportunistic CT-based screening is typically validated on scans acquired under a controlled, single-centre protocol. Such a model is one of the few realistic routes to bone-fragility assessment for war-affected and displaced individuals, for whom densitometry and longitudinal records are typically unavailable while trauma and triage computed tomography (CT) is performed abundantly. Deploying the model in that setting, however, means deploying it precisely where acquisition protocol cannot be enforced: a field hospital, a mobile scanner, equipment received through international donation, or any centre where staffing and calibration are constrained. The acquisition parameters the model implicitly relies on, radiation dose, in-plane resolution and slice

thickness, are then no longer under the developer's control. Which representation of vertebral bone remains discriminative when the scan itself, rather than the patient population, changes is therefore a directly actionable question: how does each representation behave under a controlled degradation of the scan, of the kind a field or resource-constrained centre would actually produce.

This paper answers that question directly. Rather than comparing two already acquired cohorts, synthetic degradation is applied under experimenter control to the same CT volumes, at graded severities, along three physically distinct axes: photon noise, in-plane spatial resolution and slice thickness. This design isolates each acquisition parameter and locates, where one exists, the severity at which a representation's discrimination breaks down, which a single before/after comparison cannot do.

The contribution is threefold. First, a paired train-clean, test-degraded protocol is formalised that isolates the effect of acquisition quality from sampling variability, using a patient-clustered bootstrap on the paired predictions. Second, dose-response curves across ten graded conditions on two cohorts show that this vulnerability is specific to spatial resolution and does not extend to photon noise. Third, replicating the experiment on a second, anatomically distinct cohort shows that the in-plane blur component of this vulnerability is a general property of the radiomics representation, reproducing with comparable or greater severity regardless of how much signal that representation carries in the domain concerned, while the slice-thickness component is more conditional, a distinction with direct consequence for which acquisition parameter deserves protocol-level attention when the deployment domain is unknown in advance.

II. RELATED WORK

Opportunistic use of routine CT for skeletal assessment is established for a single mean-attenuation biomarker [1], [2] and has been extended with machine-learning models built on texture, morphometry and bone-muscle features [3], [4], typically validated by automated segmentation pipelines [5]. The robustness of hand-crafted radiomics features to acquisition parameters, reconstruction kernel, slice thickness and scanner manufacturer, has been studied directly in the wider radiomics literature, which repeatedly reports that grey-level texture descriptors are among the least reproducible feature classes across protocols [6], motivating the Image Biomarker Standardisation Initiative [7]. What is missing from that literature is a graded, paired dose-response characterisation tied to a specific clinical discrimination task and evaluated against an explicit deployment motivation, namely a setting in which acquisition cannot be standardised at all. The present paper supplies exactly that characterisation for CT-based vertebral fragility screening.

III. PROBLEM STATEMENT

Let a clean CT volume for patient p yield, for each vertebra, a feature vector x under representation R , and let a degradation operator D at severity level s produce a degraded volume from which the same representation yields x' . A predictor f trained only on clean features from a training cohort is applied to the held-out vertebrae of a test cohort twice, once to their clean features and once to their degraded features,

$$\hat{y} = f(x) \in [0,1], \quad \hat{y}' = f(x') \in [0,1], \quad (1)$$

and the quantity of interest is the paired change in discrimination on the identical held-out rows,

$$\Delta = \text{AUC}(y, \{\hat{y}'_i\}) - \text{AUC}(y, \{\hat{y}_i\}). \quad (2)$$

Because both terms are computed on the same vertebrae, a patient-clustered bootstrap that resamples whole patients and recomputes both areas on each resample yields a confidence interval on Δ directly, without the independence assumption a comparison of two unrelated cohorts would require. An interval that excludes zero indicates a representation whose discrimination is not preserved under that degradation; an interval containing zero indicates that no loss is detectable at the sample size available, which is not proof of exact invariance.

IV. MATERIALS AND METHODS

A. Cohorts and Imaging Representations

Two single-centre retrospective cohorts, drawn from the segmentation and feature-extraction pipeline described in [8], [9], are studied: a lumbar-spine cohort (106 patients, 478 vertebrae) and an opportunistic abdominal cohort (126 patients, 589 vertebrae). Four representations of the segmented trabecular core [5] are compared: $R1$, the mean attenuation of the core (one feature); $R2$, the mean attenuation of three concentric zones obtained by distance-transform partitioning, together with a cortical-trabecular gradient profile (seven features); $R3$, the standards-compliant PyRadiomics original-image feature block [7], comprising 75 grey-level matrix texture descriptors, 18 first-order statistics and 14 shape descriptors (107 features); and $R4$, the full available biomarker pool reduced to the fifteen features with the highest univariate discrimination on the training cohort. $R4$ draws on a pool of 487 vertebra-derived features; muscle-derived biomarkers used elsewhere in this pipeline required a separate segmentation mask that was not available in the compute environment used for this experiment and are therefore excluded from $R4$ here.

B. Degradation Model

Three degradation families are applied to the native CT volume before feature extraction. Noise and blur are parameterised in physical units so that severity is exactly comparable across patients despite differing native voxel spacing; slice thickness is parameterised as a target in millimetres but, because it is achieved by an integer multiple of the native slice spacing, its severity is only approximately

comparable, as detailed below. Additive noise models dose reduction by adding independent Gaussian noise in Hounsfield units to every voxel

$$I'(x) = I(x) + \varepsilon(x), \quad \varepsilon(x) \sim N(0, \sigma^2), \quad (3)$$

at $\sigma \in \{15, 30, 50\}$ HU. In-plane blur models the loss of spatial resolution from a coarser reconstruction kernel or detector, applied as a two-dimensional Gaussian convolution within each axial slice with the kernel width converted from millimetres to voxels using that patient's own in-plane spacing,

$$I'(x, y, z) = (I(., ., z) * G_{\sigma_{mm}})(x, y), \quad (4)$$

at $\sigma \in \{0.5, 1, 2\}$ mm. Slice thickness models a coarser through-plane sampling by averaging native slices into non-overlapping bands of $k = \text{round}(t / \Delta z)$ slices, where Δz is the native slice spacing and t the target thickness, then repeating the band mean back across its k slices so that the array geometry is unchanged,

$$I'(x, y, z) = \frac{1}{k} \sum_{i=0}^{k-1} I(z - (z \bmod k) + i, y, x), \quad (5)$$

at $t \in \{2, 3, 5, 7\}$ mm; because this operator can only coarsen, a patient already acquired at or beyond the target thickness is left unchanged by that condition. Because k is an integer and native slice spacing varies across patients (0.5 to 3.0 mm in the lumbar cohort, 0.5 to 5.0 mm in the abdominal cohort), the achieved thickness for a given nominal condition varies by patient, and adjacent nominal levels can coincide for a given patient: in this study 39% of lumbar patients and 85% of abdominal patients receive an identical degraded volume under the nominal 2 mm and 3 mm conditions. The nominal thickness labels therefore denote a lower bound on the target rather than a spatially uniform degradation, unlike the noise and blur families. Each condition is applied once per patient and every vertebra of that patient is re-extracted from the resulting volume with the identical segmentation mask used for the clean extraction, so that the degradation is the only variable that differs between the paired feature sets.

C. Evaluation Protocol

For every condition and cohort, a regularised logistic regression with a 12 penalty and class weighting is trained by five-fold patient-grouped cross-validation on that cohort's clean features, giving the in-domain reference; the out-of-fold

model of each fold is then applied to the degraded features of the same held-out vertebrae, giving the paired degraded prediction. Missing values are imputed by the training-fold median and features standardised on the training fold; for $R4$ the fifteen features are selected on the training fold only. Uncertainty on Δ is obtained by 2000 patient-clustered bootstrap resamples (Section III). Hyperparameters are held fixed rather than tuned, and all models are fitted with scikit-learn 1.7.2 under a fixed random seed of 42.

V. RESULTS

A. Lumbar Cohort: Dose-Response

On the lumbar cohort the clean in-domain area under the ROC curve is 0.732, 0.716, 0.710 and 0.720 for $R1$ through $R4$. Table I and Fig. 1 report the paired delta at every condition. Additive noise produces at most a negligible effect: every $R1$ and $R2$ interval contains zero, $R3$ moves by at most -0.012 with its widest interval (-0.037, +0.014) also containing zero, and $R4$ shows one boundary interval at 30 HU, -0.005 (-0.013, -0.000), not preceded by a comparable shift at 15 HU or followed by one at 50 HU. Spatial-resolution loss behaves entirely differently for $R3$ alone: at 0.5 mm blur the interval still contains zero, but at 1 mm it narrows to (-0.107, +0.012) and at 2 mm it excludes zero at -0.096 (-0.165, -0.025); slice thickness shows the same pattern, with the interval at 2 mm containing zero, -0.051 (-0.087, -0.015) at 3 mm, and -0.091 (-0.137, -0.044) at 5 mm. $R1$ remains within the null interval at every one of the ten conditions. Across all ten conditions, $R2$ and $R4$ each cross it once, at the isolated points addressed below; within the blur and thickness families specifically, $R4$ never departs from the null interval.

Two features of the dose-response curves deserve comment. The thickness interval at 7 mm (-0.122, -0.020) is milder than at 5 mm (-0.137, -0.044); the two intervals overlap substantially and the difference should not be read as recovery at coarser thickness, but as bootstrap noise on the tail of the curve. Separately, two isolated intervals formally exclude zero without support from an adjacent condition: $R2$ at 3 mm thickness, +0.009 (+0.001, +0.017), and $R4$ at 30 HU noise, -0.005 (-0.013, -0.000). With forty representation-by-condition comparisons on this cohort alone, roughly two such intervals are expected by chance at the 95% level even under a true null, so neither is read as a genuine effect of coarser slices on the zone descriptor or of moderate noise on the selected pool.

B. Abdominal Cohort: Replication Test

The lumbar result predicts a specific and falsifiable pattern: on any second cohort, noise should again have no effect and spatial-resolution loss should again selectively damage R3. Table II

reports the outcome on the abdominal cohort, whose clean in-domain areas under the ROC curve are 0.665, 0.645, 0.644 and 0.640 for R1 through R4, all lower than their lumbar counterparts.

TABLE I. PAIRED DELTA (DEGRADED MINUS CLEAN AUC ON IDENTICAL ROWS) FOR THE RADIOMICS BLOCK R3, LUMBAR COHORT, WITH 95 % PATIENT-CLUSTERED BOOTSTRAP CI. R1 IS WITHIN THE NULL INTERVAL AT EVERY CONDITION; R2 AND R4 EACH DEPART FROM IT AT ONE ISOLATED CONDITION, DISCUSSED IN THE TEXT

Condition	Clean → degraded AUC	Δ (95 % CI)
Noise 15 HU	0.710 → 0.710	-0.000 (-0.016, +0.016)
Noise 30 HU	0.710 → 0.698	-0.012 (-0.037, +0.014)
Noise 50 HU	0.710 → 0.712	+0.002 (-0.023, +0.030)
Blur 0.5 mm	0.710 → 0.717	+0.007 (-0.035, +0.051)
Blur 1 mm	0.710 → 0.662	-0.048 (-0.107, +0.012)
Blur 2 mm	0.710 → 0.614	-0.096 (-0.165, -0.025)
Slice $\geq$ 2 mm	0.710 → 0.687	-0.023 (-0.053, +0.007)
Slice $\geq$ 3 mm	0.710 → 0.659	-0.051 (-0.087, -0.015)
Slice $\geq$ 5 mm	0.710 → 0.619	-0.091 (-0.137, -0.044)
Slice $\geq$ 7 mm	0.710 → 0.640	-0.070 (-0.122, -0.020)

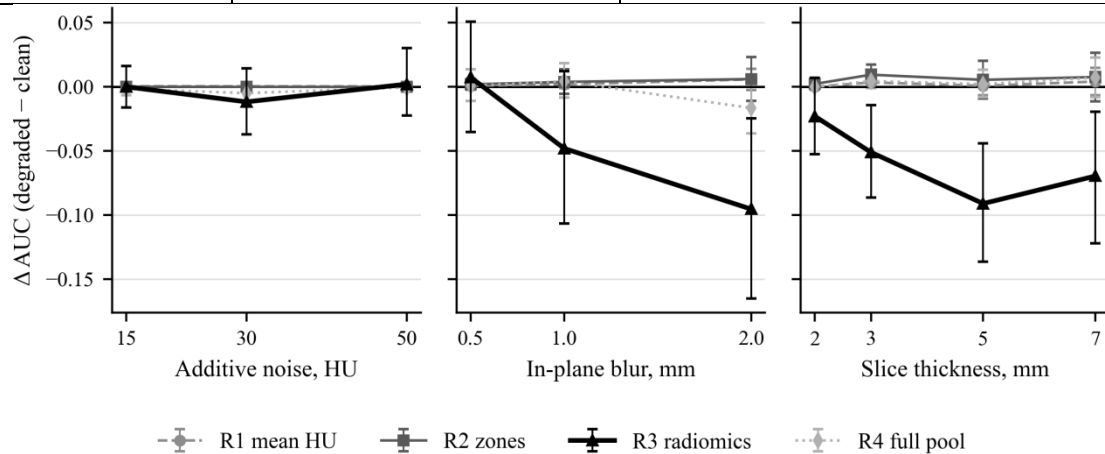


Fig. 1. Dose-response of the paired delta AUC (degraded minus clean) on the lumbar cohort, by degradation family. Points are means, error bars are 95 % patient-clustered bootstrap confidence intervals. Only the radiomics block (R3, black) shows a detectable, dose-dependent loss, confined to the two spatial-resolution families; additive noise produces at most one isolated, non-dose-dependent deviation (R4, Section V-A) and no effect on R1, R2 or R3

TABLE II. PAIRED DELTA FOR R3, ABDOMINAL COHORT, SAME LAYOUT AS TABLE I. R1 AND R2 REMAIN WITHIN THE NULL INTERVAL AT EVERY CONDITION TESTED; R4 IS ALSO AFFECTED BY IN-PLANE BLUR, MORE MILDLY THAN R3 (SEE TEXT)

Condition	Clean → degraded AUC	Δ (95 % CI)
Noise 15 HU	0.644 → 0.657	+0.013 (-0.002, +0.029)
Noise 30 HU	0.644 → 0.645	+0.001 (-0.026, +0.025)
Noise 50 HU	0.644 → 0.602	-0.041 (-0.079, -0.006)
Blur 0.5 mm	0.644 → 0.650	+0.006 (-0.018, +0.031)
Blur 1 mm	0.644 → 0.598	-0.046 (-0.090, -0.002)
Blur 2 mm	0.644 → 0.532	-0.112 (-0.169, -0.053)
Slice $\geq$ 2 mm	0.644 → 0.646	+0.002 (-0.016, +0.022)
Slice $\geq$ 3 mm	0.644 → 0.648	+0.004 (-0.015, +0.023)
Slice $\geq$ 5 mm	0.644 → 0.640	-0.004 (-0.037, +0.028)
Slice $\geq$ 7 mm	0.644 → 0.625	-0.019 (-0.056, +0.019)

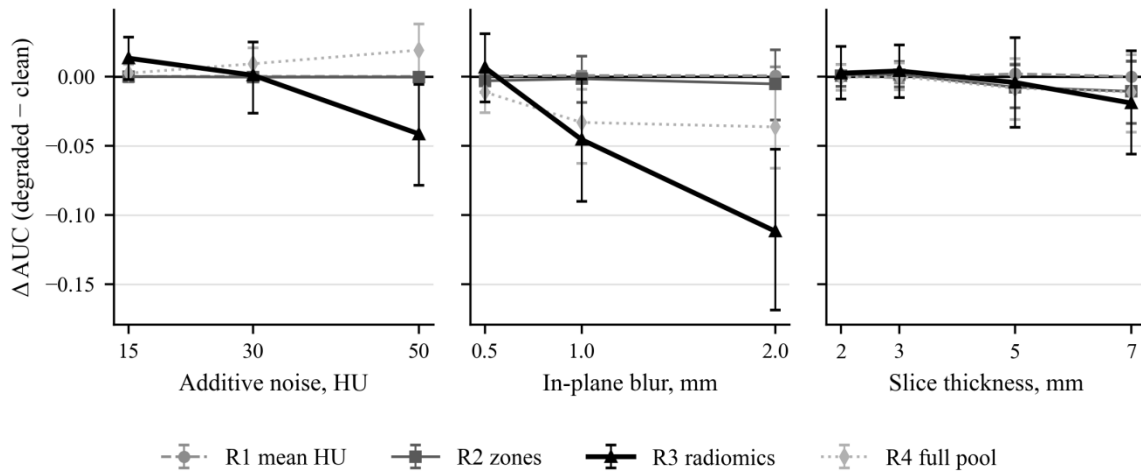


Fig. 2. Dose-response on the abdominal cohort, same layout as Fig. 1. In-plane blur reproduces the lumbar-cohort collapse of the radiomics block ($R3$, black) with an earlier onset and, more mildly, draws down the selected full-pool representation ($R4$); slice thickness and additive noise show no comparable, dose-consistent effect

The blur component of the prediction replicates, and does so more severely than in the lumbar cohort. $R3$ is within the null interval at 0.5 mm, -0.046 (-0.090 , -0.002) at 1 mm and -0.112 (-0.169 , -0.053) at 2 mm, a threshold one step earlier and a terminal loss larger than the -0.096 observed in the lumbar cohort, despite $R3$ carrying substantially less in-domain signal here (0.644 against 0.710). $R4$ is also affected under blur in this cohort, -0.033 (-0.063 , -0.009) at 1 mm and -0.036 (-0.066 , -0.006) at 2 mm, unlike in the lumbar cohort where $R4$ stayed within the null interval at every blur level; the reduced feature pool therefore does not confer the same acquisition robustness in both cohorts. The thickness component of the prediction does not replicate: no interval for $R3$ or $R4$ excludes zero at any thickness tested, up to and including 7 mm, and neither curve shows a monotonic trend. $R1$ and $R2$ again remain within the null interval at every condition. Two isolated intervals exclude zero outside the blur family, $R3$ at 50 HU noise, -0.041 (-0.079 , -0.006), and $R4$ at 50 HU noise, $+0.019$ (0.000 , $+0.038$); with eighty representation-by-condition comparisons across the two cohorts roughly four such intervals are expected by chance at the 95 % level, and these two, of opposite sign, not preceded by a trend at 15 or 30 HU, and outside the family in which every other effect in this study was found, are treated as such chance occurrences rather than a genuine noise sensitivity.

C. A General Vulnerability and a Cohort-specific One

In-plane blur and slice thickness behave differently once tested on a second cohort, and that difference is informative. Blur destroys the radiomics representation's discrimination in both

cohorts, with a dose-response curve of comparable shape and, if anything, greater severity in the cohort where $R3$ carries less in-domain signal to begin with (0.644 in the abdominal cohort against 0.710 in the lumbar cohort). This rules out the simplest explanation for a representation-level vulnerability, that it is proportional to how much signal the representation carries in that domain; blur damage instead looks like a property of the representation itself, consistent with a texture matrix computed from local grey-level co-occurrence being directly and mechanically smoothed by in-plane blur regardless of how much of that texture is diagnostic in a given cohort. Slice-thickness coarsening, by contrast, required a more extreme nominal degradation to reach a comparable loss, -0.091 at 5 mm against -0.096 already at 2 mm of blur (the two conditions are not on a common physical scale, so this compares severity level rather than magnitude), and was not detectable at all in the abdominal cohort at any thickness tested. Because a through-plane averaging operator and an in-plane texture matrix interact in a more anatomy-dependent way than a direct in-plane smoothing does, and because the true thickness effect, where present, is smaller and therefore harder to resolve against the same sample size, the absence of a detectable thickness effect in the abdominal cohort cannot be distinguished, with the data available here, from a true absence and from a true but smaller effect that this cohort's sample size does not resolve.

VI. DISCUSSION

The central finding is that in-plane spatial resolution, not photon noise, is the acquisition parameter that a texture-dependent screening model cannot survive, and that this specific vulnerability is not a quirk of one cohort: it reproduced, with

comparable or greater severity, in a second, anatomically distinct cohort in which the radiomics representation carried substantially less discriminative signal to begin with. Dose reduction, which primarily adds noise, appears to be compatible with all four representations tested here, in both cohorts. A thicker slice protocol damaged the radiomics representation in the lumbar cohort but not detectably in the abdominal cohort, a more tentative finding given the smaller effect size involved. For a deployment context in which acquisition protocol is unknown in advance, precisely the situation this line of work targets, the replicated blur vulnerability argues for building the screening model on the mean-attenuation representation, which showed no detectable vulnerability to any of the ten conditions tested on either cohort, or on the concentric-zone representation, which departed from that pattern only once, at an isolated condition attributable to chance (Section V-A), rather than on high-dimensional texture, whose fragility to resolution loss is now confirmed across two independent cohorts rather than resting on a single one.

The population this study targets makes acquisition unpredictability the default rather than the exception. The average age of Ukrainian servicemembers has risen from about 30–35 at the start of the full-scale invasion to 43–45 by 2024–2025 [10], [11], with more recent reporting describing further ageing, over half the personnel of at least one frontline brigade above 45 and new recruits increasingly over 55 [12]; this places the population of interest squarely in the same middle-age band as the two cohorts studied here, whose patients average 40 to 50 years in both sexes. Men of that age are also the group conventional osteoporosis pathways never reach, since screening programmes are built around postmenopausal women; a soldier who undergoes trauma or triage CT has no other realistic route to a bone-fragility assessment beyond opportunistic analysis of a scan he already received. Because a screening model for that population will encounter scanners of varying age and calibration, from stationary hospital equipment to mobile or field-deployed units and equipment received through international donation, exactly the kind of variation the blur and thickness families in this study approximate, the confirmed robustness of density-based descriptors to spatial-resolution loss is not a peripheral finding but a precondition for the intended deployment.

Where a centre's protocol is known and radiomics features are nonetheless desired for their added discrimination on cohorts in which they carry

signal, the thresholds identified here give a concrete acquisition floor. The blur threshold is well supported but differs by cohort: loss becomes detectable between $\sigma = 0.5$ and 1 mm in the abdominal cohort and only between $\sigma = 1$ and 2 mm in the lumbar cohort. A conservative floor, effective in-plane blur at or below $\sigma = 0.5$ mm, covers both. A slice-thickness floor of 2 mm, the first point of detectable loss in the lumbar cohort, is offered with lower confidence, since the same threshold produced no detectable loss in the abdominal cohort under an identically sized experiment, and since the nominal thickness labels only approximately track the achieved degradation (Section IV-B), so this floor should be read as directional rather than precise. Both thresholds are specific to the segmentation, extraction pipeline and sample sizes used here and are offered as a starting point for protocol design, not as a validated clinical specification.

Several limitations bound what may be claimed. The degradation operators are synthetic approximations of the physical processes, dose reduction, reconstruction kernel and slice protocol, that they are intended to model; a genuinely low-dose or thick-slice acquisition involves reconstruction artefacts and photon statistics that additive Gaussian noise and linear filtering do not fully reproduce. The isolated noise intervals on the abdominal cohort, although most plausibly chance occurrences given the number of comparisons, were not pre-registered as null and cannot be fully excluded as genuine, cohort-specific effects without a further, targeted replication. The absence of a detectable thickness effect in the abdominal cohort is, as discussed in Section V-C, consistent with either a true absence of that vulnerability in this cohort or an effect too small for the present sample to resolve; distinguishing the two would require a larger cohort or a finer thickness grid. Both cohorts are drawn from a single non-conflict centre; prospective evaluation on scans actually acquired under field conditions, and on cohorts of war-affected and displaced individuals, remains the necessary next step before any deployment recommendation can be considered validated rather than plausible.

VII. CONCLUSIONS

Four imaging representations of vertebral bone were evaluated under a paired, graded acquisition-degradation protocol on two independent, anatomically distinct cohorts. Additive noise, at levels spanning 15 to 50 HU, produced no detectable loss of discrimination for any representation on

either cohort. In-plane blur selectively destroyed a high-dimensional radiomics representation in both cohorts, with a comparable or greater loss in the cohort where the representation carried less in-domain signal, showing that this vulnerability is a general property of the representation rather than an artefact of one dataset; the threshold at which loss became detectable was between $\sigma = 0.5$ and 1 mm in the abdominal cohort and between $\sigma = 1$ and 2 mm in the lumbar cohort. Slice-thickness coarsening produced a smaller, dose-dependent loss for the same representation in the lumbar cohort, becoming detectable between the nominal 2- and 3 mm conditions, that did not reach detectability in the abdominal cohort. A single mean-attenuation feature was unaffected by every degradation tested in both cohorts, and a seven-feature concentric-zone descriptor departed from that pattern only once, at an isolated condition attributable to chance. For opportunistic fragility screening in war-affected and displaced populations, whose average age places them squarely in this study's patient demographic and whose acquisition conditions cannot be standardised in advance, these compact density-based descriptors remain the defensible choice, and the confirmed, cross-cohort blur vulnerability of high-dimensional texture strengthens rather than weakens that recommendation.

FUNDING AND ETHICS

This research was funded by the Latvian-Ukrainian Bilateral Cooperation Programme in Science and Technology in 2025-2026, project No. LV-UA/2025/4, registration number 0125U003179. The retrospective imaging study on which the underlying cohorts are based was approved by the Research Ethics Committee of Rīgas Stradiņa Universitāte (decision No. 2-PĒK-4/662/2025, 16 April 2025); individual informed consent was waived for the retrospective analysis of anonymised data. The authors declare no conflict of interest.

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Received: July 19, 2026

Accepted: August 12, 2026

Published: September 18, 2026

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В. М. Синєглазов, К. Д. Рязановський, Д. Орловс, Є. Степанова, А. Платкаїс. Стійкість до втрати просторової роздільної здатності при КТ-скринінгу крихкості хребців у осіб, потенційно постраждалих від війни

Роботу присвячено збереженню точності моделей машинного навчання для КТ-скринінгу крихкості хребців за умов погіршеної якості зйомки, характерної для мобільних та польових сканерів у регіонах, що постраждали від війни. У роботі запропоновано парний протокол оцінювання, у якому модель, навчену на чистих ознаках, двічі застосовують до тих самих відкладених хребців, який базується на керованій синтетичній деградації тих самих КТ-обстежень: адитивний шум (15, 30, 50 HU), розмиття в площині ($\sigma = 0,5, 1, 2$ мм) і збільшення товщини зрізу (2, 3, 5, 7 мм). У роботі розроблено порівняльне оцінювання чотирьох подань зображення хребця на двох незалежних когортах (106 пацієнтів, 478 хребців і 126 пацієнтів, 589 хребців), де парну різницю площі під ROC-кривою оцінюють кластерним бутстрепом за пацієнтами. Адитивний шум не дав послідовного ефекту. Розмиття в площині знизило площу під кривою радіомічного подання на 0,096 (95 % ДІ $-0,165, -0,025$) і на 0,112 ($-0,169, -0,053$) у поперековій та черевній когортах, тоді як подання на основі середнього ослаблення лишилося в межах нульового інтервалу за всіх умов (на чистих даних 0,732 і 0,665). Результати роботи може бути використано для добору стійких до умов зйомки візуальних біомаркерів для опортуністичного скринінгу постраждалих від війни та переміщених осіб, середній вік яких збігається з віком досліджених когорт і яких обстежують там, де є обладнання.

Ключові слова: машинне навчання, комп’ютерна томографія, деградація зображення, крихкість хребців, зсув домену, радіоміка, потенційно постраждалих від війни, опортуністичний скринінг.

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