Review Paper
Applications of Wavelet transforms in Radiomic Feature Extraction from Medical Images: A Systematic Review

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ABSTRACT

Background: Radiomics relies on quantitative information extracted from medical images to enhance clinical decision-making; however, it is subject to noise, artifacts, and varying imaging protocols, all of which affect its reliability. Wavelet transforms provide a solution by allowing images to be decomposed into multiscale frequency components while retaining spatial information. Compared to classical preprocessing methods, this work highlights the necessity of an overall precondition framework for using wavelet transforms in radiomics.

Methods: In this study, we conducted a review by systematically searching databases, such as PubMed, IEEE Xplore, Web of Science, and Scopus for peer-reviewed articles published between January 2015 and February 2025. We focused on keywords, like "wavelet transform," "radiomics," "feature extraction," and specific imaging modalities, such as "CT," "MRI," and "PET." We selected studies based on their relevance to wavelet-based radiomics and evaluated their quality using a modified QUADAS-2 tool.

Results: Our findings indicated that wavelet transforms can significantly enhance the reproducibility of radiomic features, minimize sensitivity to noise, and improve the detection of textural and morphological patterns in CT, MRI, and PET imaging. However, in certain situations, alternative methods, like empirical mode decomposition or short-time Fourier transform may yield better results. Wavelet transforms often surpass traditional Fourier transform techniques by offering localized and scale-dependent decomposition, even though they come with increased computational demands.

Conclusion: This review offers a thorough framework for wavelet-based radiomics, merging mathematical concepts with practical implementation strategies. It contributes to the field by providing clear approaches for optimizing parameters and extracting features, ultimately aiding researchers and clinicians in enhancing medical imaging analysis for precision medicine.

Keywords: Wavelet transform, Radiomics, Feature extraction, Medical imaging, Multiresolution analysis

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Introduction

Medical imaging techniques, such as CT, MRI, and PET play a crucial role in facilitating accurate diagnosis, treatment planning, and monitoring [1]. Radiomics enhances these capabilities by extracting quantitative features from images, which provide valuable insights into tissue characteristics and disease progression, ultimately supporting personalized medicine. However, the field of radiomics faces several challenges, including sensitivity to noise and issues with reproducibility across different imaging protocols [2].

Wavelet transforms offer a solution to these challenges by breaking down images into multiscale frequency components. This approach helps preserve spatial details and enhances the robustness of features compared to traditional methods, like Fourier transform. Despite their advantages, wavelet methods can introduce computational complexity and difficulties in parameter selection, which can limit their widespread application [3].

Wavelet-based techniques, grounded in mathematical principles, enable detailed analysis for extracting multiresolution radiomic features. They are particularly effective in detecting subtle patterns and ensuring the reproducibility of features. Ongoing advancements make these methods even more efficient [4]. When wavelet transforms decompose an image into approximation (low-frequency) and detail (high-frequency) components, they allow for the isolation of meaningful structural data while reducing noise and irrelevant variance [5, 6]. This dual capability makes wavelets an optimal tool for radiomics, especially since biologically relevant features need to be platform-agnostic, considering the challenges posed by data heterogeneity across institutions and imperfections in imaging modalities [7].

This review describes wavelet transforms role in extracting robust radiomic features from CT, MRI, and PET images. We outline practical workflows using PyWavelets and MATLAB, address challenges, like parameter selection, computational complexity, and standardization, and propose adopting IBSI guidelines for standardized analysis. This review aimed to guide researchers and clinicians to enhance precision medicine through improved medical imaging analysis.

Methods

This review systematically evaluated the application of wavelet transforms for radiomic feature extraction in medical imaging, focusing on their mathematical foundations and practical implementation. The review adhered to a structured methodology to ensure comprehensive coverage of relevant literature, as outlined below.

Comparison with existing reviews

This review stands out from previous literature by providing a specialized and in-depth review of wavelet transforms, with a particular focus on their application in medical images for radiomic feature extraction, a role that has not been extensively covered elsewhere. Grobbelaar et al. concentrate on utilizing wavelet transforms for denoising EEG signals [8], while Guo et al. trace the evolutionary history of wavelet theory and examine its diverse properties in detail [9]. Manikandan and Dandapat investigate wavelet-based techniques for ECG compression, evaluating their effectiveness [10], and Serhal et al. offer a comprehensive review of AI models applied to analyze atrial fibrillation using wavelet transform [11]. In contrast, Shuvo et al. address a broader spectrum, encompassing the analysis of both medical signals and images across various healthcare applications [12]. The innovation of this approach lies in the detailed examination of various wavelet transform transforms—discrete (DWT), continuous (CWT), tunable q-factor wavelet transform (TQWT), and advanced transforms—that are specifically designed for radiomics applications and achieve high performance metrics. Furthermore, the integration of machine learning (ML) and deep learning (DL) with wavelet transform, provides significant insights, making it a valuable resource for advancing radiomics research and clinical practice. As shown in Table 1, this review uniquely focused on radiomics in medical images, filling a gap in the existing literature.

Search strategy

A systematic literature search was conducted using PubMed, IEEE Xplore, Web of Science, and Scopus databases to identify peer-reviewed articles published between January 2015 and February 2025. The search utilized a combination of keywords, including "wavelet transform", "radiomics", "feature extraction", "medical imaging", "multiresolution analysis", "2D DWT", "3D DWT", "texture analysis", and "image preprocessing". These terms were refined with modality-specific keywords (e.g. "CT", "MRI", "PET") to target studies relevant to medical imaging applications. Boolean operators (AND, OR) were employed to combine terms, and filters were applied to limit results to English-language articles and peer-reviewed journals. Additional sources were identified through manual screening of reference lists from key articles.

Table 1. Comparative summary of existing reviews on wavelet applications

Authors (y)	Main Objective	Type of Medical Data	Types of Wavelet Transforms	No. of Citations	Other Aspects
Grobbelaar et al. (2022) [8]	Survey denoising techniques for EEG signals using wavelet transform	EEG signals	General wavelet denoising methods	101	Focus on noise removal in neurophysiology; limited to EEG; no radiomics emphasis
Guo et al. (2022) [9]	Review development history and properties of wavelet theory	General signals	Various wavelet constructions	410	Broad theoretical overview; not medical-specific; challenges and opportunities discussed
Manikandan and Dandapat (2014) [10]	Prospective review of wavelet-based ECG compression methods	ECG signals	Wavelet-based compression techniques	153	Emphasis on compression performance; ECG-specific; performance metrics evaluated
Serhal et al. (2021) [11]	Overview of wavelet and AI for atrial fibrillation prediction/detection on ECG	ECG signals	Wavelets with AI for atrial fibrillation	54	Integration with AI; focused on atrial fibrillation; prediction and classification
Shuvo et al. (2025) [12]	Systematic review of wavelet and AI in healthcare	Medical signals and images	Wavelet transformation with AI	0 (new)	Broad healthcare applications; includes signals and images; systemic review approach

Figure 1 outlines the stages of identification, screening, eligibility, and inclusion, with reasons for exclusions at each stage.

Selection criteria

Studies were included if they: 1) focused on the application of wavelet transforms in radiomic feature extraction for medical imaging, 2) provided mathematical or practical insights into wavelet transform implementations (e.g. 2D or 3D discrete wavelet transform), 3) addressed textural or morphological feature extraction in modalities, such as CT, MRI, or PET, and 4) were published within the specified timeframe. Exclusion criteria encompassed: 1) studies lacking a clear focus on wavelet-based radiomics, 2) non-peer-reviewed sources (e.g.

conference abstracts, editorials), 3) studies not involving medical imaging, and 4) articles not available in English. The selection process is summarized in a flow diagram (Figure 1), detailing the number of studies screened, included, and excluded at each stage. The inclusion and exclusion criteria based on the PICOS framework (population, intervention, comparison, outcome, study design) are given in Table 2. This PICOS-based table complements the PRISMA flow diagram (Figure 1), ensuring a structured approach to study selection.

Data extraction

To ensure consistency, we extracted data from the included studies using a standardized template. The information gathered included: 1) the type of study (such

Table 2. Inclusion and exclusion criteria based on the PICOS framework

PICOS Element	Inclusion Criteria	Exclusion Criteria
Population	Studies on medical imaging data (e.g. CT, MRI, PET) for radiomics in human diseases	Studies not involving medical imaging or radiomics; non-human or non-clinical data
Intervention	Application of wavelet transforms (e.g. DWT, CWT, 2D/3D) for feature extraction	Studies without wavelet transforms or not focused on radiomic feature extraction
Comparison	Comparisons with classical methods (e.g. Fourier Transform) or no comparison required if wavelet-focused	Studies without relevance to wavelet-based radiomics comparisons
Outcome	Outcomes related to feature reproducibility, noise reduction, texture/morphology detection, or diagnostic performance	Outcomes not related to radiomics features or medical imaging analysis
Study design	Peer-reviewed articles, systematic reviews, methodological studies (2015–2025)	Non-peer-reviewed (e.g. abstracts, editorials), non-English, pre-2015 or post-2025

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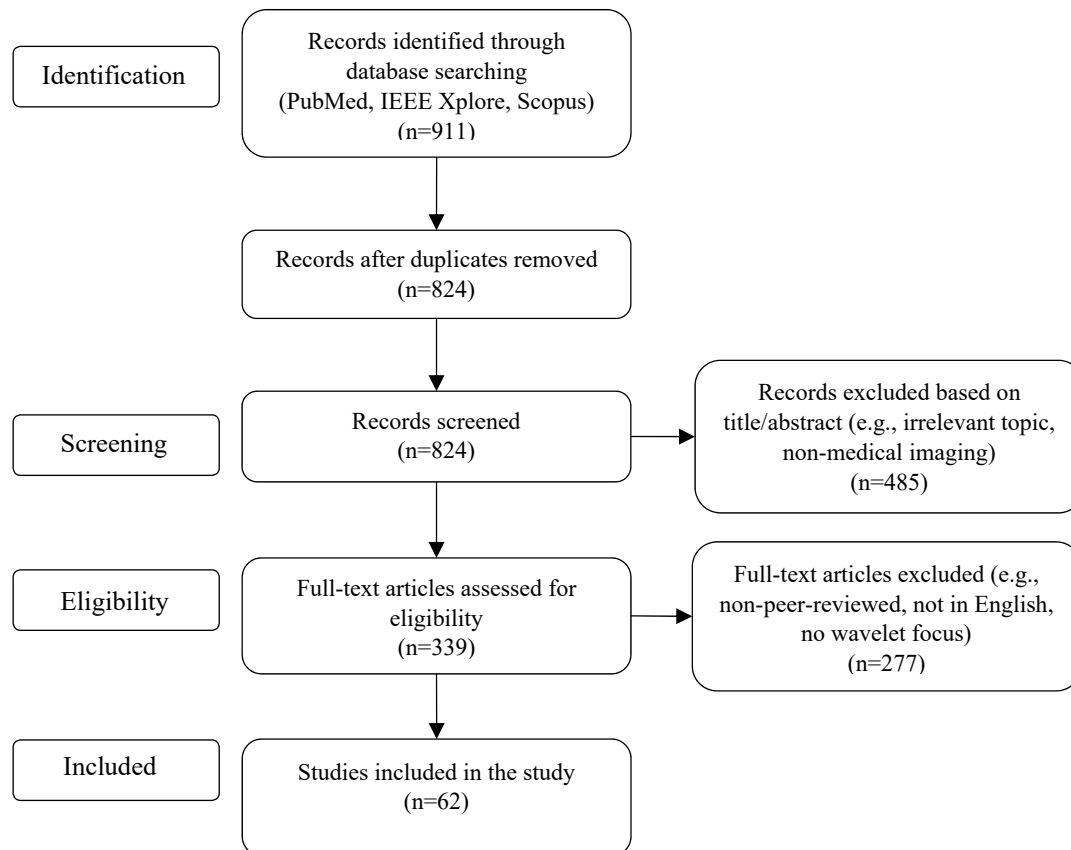
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Figure 1. Flow diagram illustrating the study selection process for the systematic review on wavelet filters in radiomic feature extraction

as methodological or applied), 2) the imaging modality used (CT, MRI, or PET), 3) the type of wavelet filter applied (like Haar, Daubechies, or Symlets), 4) the specific radiomic features extracted (for example, intensity-based features, gray-level co-occurrence matrix [GLCM], or shape-based features), 5) the computational tools utilized (such as PyWavelets or MATLAB), and 6) the reported outcomes (including feature reproducibility and diagnostic performance). For studies that involved practical implementations, we also recorded details about preprocessing steps, decomposition levels, and feature extraction workflows. Two reviewers independently extracted the data, and any discrepancies were resolved through discussion to ensure accuracy.

Quality assessment

We assessed the quality of the included studies using a modified version of the quality assessment of diagnostic accuracy studies (QUADAS-2) tool, adapted for radiomics research. The evaluation focused on: 1) the clarity of the methodology (for instance, how well the wavelet transform implementation was described),

2) the robustness of the results (such as reproducibility across different imaging protocols), 3) the relevance to radiomics applications, and 4) adherence to standardized reporting practices, like the image biomarker standardization initiative (IBSI) guidelines. Based on these criteria, studies were categorized as high, moderate, or low quality, with only high- and moderate-quality studies included in the final synthesis to ensure reliability.

Risk of bias assessment

To systematically evaluate the potential for bias in the included studies, we conducted a risk of bias assessment using a tailored framework adapted from the QUADAS-2 tool and radiomics-specific guidelines. This assessment focused on four key domains:

Selection bias: We examined whether the study populations were representative of the target clinical scenarios and whether inclusion/exclusion criteria were clearly defined. Studies with narrowly defined cohorts or lacking modality-specific justification were flagged as high risk.

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Performance bias: We evaluated the transparency and reproducibility of wavelet transform implementation, including the choice of wavelet type, decomposition levels, and preprocessing steps. Studies that failed to report these parameters or used non-standardized workflows were considered as higher risk.

Detection Bias: We assessed whether the radiomic features extracted were validated against clinical or biological outcomes. Studies lacking validation or relying solely on internal metrics (e.g. area under the curve [AUC] without external testing) were marked as moderate to high risk.

Reporting bias: We reviewed adherence to reporting standards, such as the IBSI. Studies that omitted key methodological details or failed to disclose software tools and parameter settings were considered at risk of incomplete reporting.

Each study was independently reviewed by two authors, and disagreements were resolved through consensus. The overall risk of bias was categorized as low, moderate, or high based on the cumulative assessment across domains.

Data analysis

We comprehensively provided an overview of how wavelet filters are applied in radiomics. The analysis fo-cused on: 1) practical workflows for feature extraction across different imaging modalities, and 2) challenges, such as parameter selection and standardization. We grouped studies by modality (CT, MRI, and PET) and wavelet type to identify patterns in feature extraction and implementation strategies. Key findings were summarized in tables to facilitate comparison. We highlighted qualitative trends in feature reproducibility, noise reduction, and clinical applicability. This narrative synthesis integrates theoretical insights with practical guidance, bridging mathematical rigor with real-world applications in radiomics.

Results

The mathematical foundations of wavelet transforms

The mathematical foundations of wavelet transforms, which include CWT, DWT, and multiresolution analysis allows us to concentrate on practical applications [13-15]. These foundational concepts highlight the unique advantages of wavelet transforms in the field of radiomics, providing superior time-frequency analysis and localized, scale-dependent decomposition compared to traditional methods, like the Fourier transform. This capability facilitates the robust extraction of biologically relevant features, thereby enhancing the practical implementation of wavelet-based radiomic workflows [16].
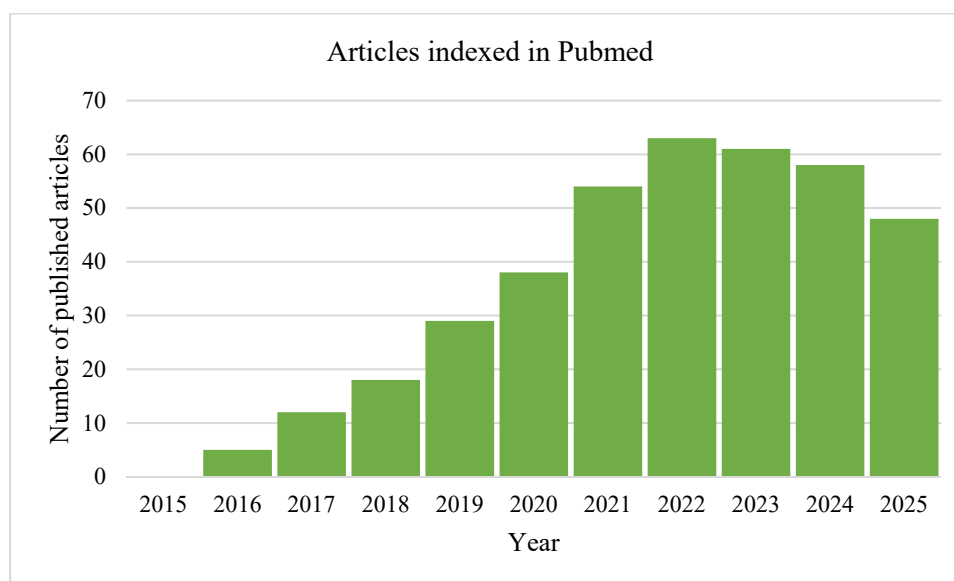

Figure 2. Annual number of published papers in wavelet-based radiomics from 2015 to 2025, based on PubMed search results for "wavelets and radiomics

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Wavelet transforms in radiomic feature extraction

Wavelet transforms have become a cornerstone of radiomics, enabling multiscale decomposition of medical images to extract biologically meaningful features. To examine this important issue in recent years, a PubMed search using the keywords "wavelets and radiomics" from 2015 to 2025 can show the status and trend of publishing articles in this field (Figure 2). This section highlights the role of wavelets in texture enhancement, noise reduction, feature diversity, advanced transform design, and clinical applications.

Wavelet transforms enhance the detection of subtle textural and morphological patterns often missed by conventional methods [17]. Texture, defined as the spatial arrangement of pixel intensities, is essential for distinguishing healthy from pathological tissue [18]. Through decomposition into approximation and detail subbands [19], wavelets capture both broad structural patterns (e.g. tumor shape) and fine-grained details (e.g. edges, granularity) [20, 21]. This multiscale capability allows radiomics to integrate microscopic and macroscopic features [22, 23].

Wavelet decomposition improves feature robustness by isolating high-frequency noise into detail subbands, allowing selective filtering while preserving signal integrity [24-26]. This is particularly beneficial in noisy imaging environments or multi-center studies [27]. Wavelet-based features have demonstrated higher reproducibility across scanners and protocols, supporting their clinical reliability [28, 29].

Wavelet transforms facilitate the extraction of diverse radiomic features across decomposition levels. Approximation subbands yield intensity metrics (e.g. mean, variance) [30], while detail subbands support texture analysis via GLCM-derived metrics, like contrast and entropy [31]. Shape features, such as compactness and eccentricity, are refined through edge detection in detail components [32, 33]. A typical three-level DWT yields eight subbands, each offering unique insights into image structure [14].

Beyond classical DWT and CWT, advanced transforms enhance radiomic performance. The dual-tree complex wavelet transform (DTCWT) improves directional selectivity and shift-invariance, aiding feature extraction in MRI and PET [34]. The TQWT wavelet transform (TQWT) allows adaptive tuning for modality-specific tasks, like tumor heterogeneity analysis [12]. These methods address limitations, such as boundary ef-

fects and noise sensitivity, and are increasingly adopted in radiomics workflows.

Wavelet-based radiomics has shown promise across CT, MRI, PET, and ultrasound:

In CT, wavelet features improve classification of hepatocellular carcinoma [35], enhance pulmonary lesion grading in COVID-19 [19], and predict treatment response in rectal cancer [36].

In MRI, DWT features combined with convolutional neural network (CNNs) support brain tumor classification [37], while 3D wavelet filters aid glioma grading [38].

In PET, wavelet features enhance biclustering in breast cancer [39] and enable parametric imaging with improved filtering [40].

In ultrasound, wavelet decomposition differentiates malignant from benign prostate tissue [41]. These studies underscore the diagnostic and predictive value of wavelet integration in radiomics.

Wavelet transforms enrich radiomic analysis by capturing textural and structural characteristics, improving robustness, and enabling multiscale feature representation. Their versatility across CT, MRI, and PET imaging modalities further validates their utility [42]. The following sections provide practical guidance for integrating wavelet transforms into radiomics workflows.

Practical guide to implement wavelet transforms in radiomics workflows

The application of wavelet transforms into radiomics workflows needs to be systematic to ensure that extracted features are interpretable and reproducible. This section presents a step-by-step guide as to how to apply wavelet transforms from preprocessing to feature selection, as well as useful tools and practical examples. By following these steps, researchers and practitioners can use the wavelet transforms in radiomics workflow for various imaging modalities and also address the challenges of computing large volumes of medical images. A summary of these steps is represented in Figure 3. The Haar wavelet, known for its simplicity and blocky structure, effectively captures abrupt changes and edges. Daubechies wavelets, characterized by vanishing moments, are suited for texture analysis and noise reduction, while Symlets provide a symmetric alternative preserving signal symmetry. The DWT decomposes images into

subbands (e.g. LL, LH, HL, and HH) for detailed analysis. Texture features can be extracted using the GLCM, a statistical method based on pixel intensity relationships. The IBSI ensures consistent imaging biomarker extraction. Principal component analysis (PCA) reduces feature dimensionality while maintaining variance.

Step-by-step process for applying wavelet transforms

Image preprocessing and normalization

Medical imaging preprocessing can be divided into low-level and high-level techniques. Low-level preprocessing typically involves steps, such as filtering, registration, normalization, and segmentation to prepare the raw medical images. In contrast, high-level preprocessing methods, such as wavelet transform models or empirical mode decomposition techniques, are applied to further enhance data quality, thereby improving the accuracy of diagnosis and prognosis.

Selection of wavelet type and decomposition levels

The choice of wavelet type and decomposition levels is crucial in analysis. Haar is best for sharp edges, while daubechies (DB) and Symlets suit gradual transitions and textures. The number of levels (usually 1–4 for 2D images) depends on the desired scale of detail, with lower levels capturing finer, high-frequency features and higher levels representing coarser, low-frequency components. Image size constrains the maximum number of levels (e.g. a 256×256 image allows up to 8 levels). Optimal selection requires testing different configurations and validating against reference data.

Application of the wavelet transform and feature extraction

The preprocessed image, whether 2D (CT/MRI slice) or 3D (volume), undergoes a DWT to decompose it into multiple sub-bands. In 2D, DWT produces four sub-bands (LL, LH, HL, HH), with multilevel decomposition applied recursively to LL for finer analysis. In 3D, eight sub-bands are generated (low-low-low [LLL] and seven detail sub-bands across spatial dimensions), with repeated decomposition of LLL for multi-resolution analysis. Feature extraction may use LL or LLL for global intensity metrics, while detail sub-bands (LH/HL/HH in 2D, and the seven high-frequency components in 3D) provide rich information for texture analysis (e.g. GLCM, LBP) and shape descriptors. Features follow standards, like IBSI for consistency across 2D and 3D analyses.

Post-processing and feature selection

After feature extraction, the dataset is refined by removing irreproducible features, reducing dimensionality through methods, like PCA or correlation filtering, and normalizing data for ML. Irreproducible features refer to those with low stability across repeated measurements or high sensitivity to noise, often assessed using metrics, like ICC or COV. This ensures a reliable, focused feature set for further analysis.

Software tools and libraries for implementation

The field of wavelet-based radiomics has benefited significantly from a growing suite of accessible tools and software, which streamline workflows for researchers and clinicians. These platforms facilitate each stage of the radiomics pipeline, from preprocessing and wavelet decomposition to feature extraction and post-processing, thereby broadening access and reducing technical barriers. A brief overview of commonly used tools is shown in Figure 4.

Python and MATLAB are the most popular platforms for wavelet-based radiomics. Python is favored for its open-source libraries (e.g. PyWavelets, PyRadiomics) and integration with ML, while MATLAB is preferred for its user-friendly interface and powerful wavelet toolbox for medical image analysis.

Wavelet transforms are widely implemented in Python via the PyWavelets library and in MATLAB using the wavelet toolbox, both providing functions for signal decomposition and reconstruction, such as wavedec and waverec. Common wavelet families, including Haar, Daubechies, and Symlet, can be applied in both environments, with adjustable filter orders (e.g. dbn with varying n). These transforms serve diverse applications, like signal compression, denoising, and feature extraction. [53-56].

Worked examples with sample datasets

CT (Lung Nodule): Segment a 64x64 ROI from a lung CT scan (e.g. LIDC-IDRI dataset). Normalize pixel intensities to [0, 1], apply a 2-level Daubechies (db4) DWT, and extract GLCM contrast from the HH2 sub-band (The "2" in "HH2" indicates the second level of decomposition). The result was an enhanced texture of nodule boundaries, which aids in the classification of malignancy [57].

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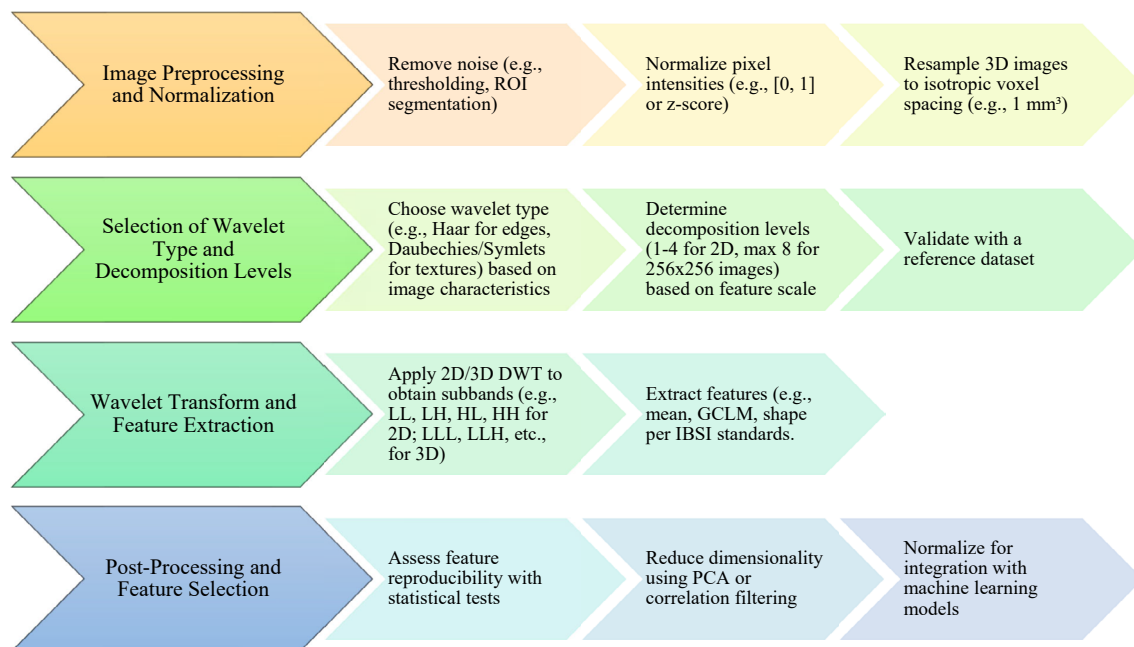
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Figure 3. Steps in radiomics feature extraction and applying wavelet transforms

MRI (brain tumor): Preprocess a 128×128 T2-weighted MRI slice (e.g. BraTS dataset, resampled to 1 mm³ isotropic voxel spacing). Apply a 3-level Symlet (sym4) DWT, and compute entropy from the LH3 subband. The result demonstrates improved detection of tumor heterogeneity, thereby supporting enhanced segmentation accuracy [58].

PET (tumor standardized uptake value (SUV) Analysis): Normalize a 32×32 ROI from a PET scan slice (e.g. TCIA dataset). Apply a 1-level Haar DWT, and extract mean intensity from the LL1 subband. The result enables the quantification of tumor metabolic activity, facilitating more accurate lesion characterization [59].

To provide an overview of recent advancements in wavelet-based techniques for medical imaging, we summarized key studies focusing on their methodologies, software tools, findings, and limitations. Table 3 presents a brief comparison of these studies, highlighting their contributions to applications, such as denoising, segmentation, classification, and image fusion across various imaging modalities, including CT, MRI, and ultrasound. In order to avoid making the table too long, these studies were randomly selected from the 62 articles mentioned in the "Methods" section.

Tips for optimizing computational efficiency and managing large datasets

This section provides practical strategies to enhance computational efficiency and handle large medical imaging datasets in wavelet-based radiomics, ensuring scalable and resource-effective analysis [80].

Key approaches include downsampling large images (e.g. reducing resolution from 512×512 to 256×256 when fine details are not critical) to balance accuracy and speed, employing parallel processing in Python or MATLAB to apply DWT across multiple ROIs or 3D slices simultaneously, limiting decomposition levels to 3 or 4 to avoid excessive computational burden with diminishing returns, managing memory by processing 3D volumes slice-by-slice and saving subbands to disk in formats, like HDF5, and utilizing batch processing with cloud computing for efficient handling of clinical-scale datasets.

Following the guideline, practitioners will have a good chance of implementing wavelet transforms in their radiomics, according to modality and research objective preferences. It is the mixture of the careful pre-processing, the wise choice of wavelets, and the easy calculation that produces scientifically strong and clinically actionable features for more profound interrogation of medical imaging data. Table 4 provides perspectives pertaining to the choice of wavelet transforms as refracted by image
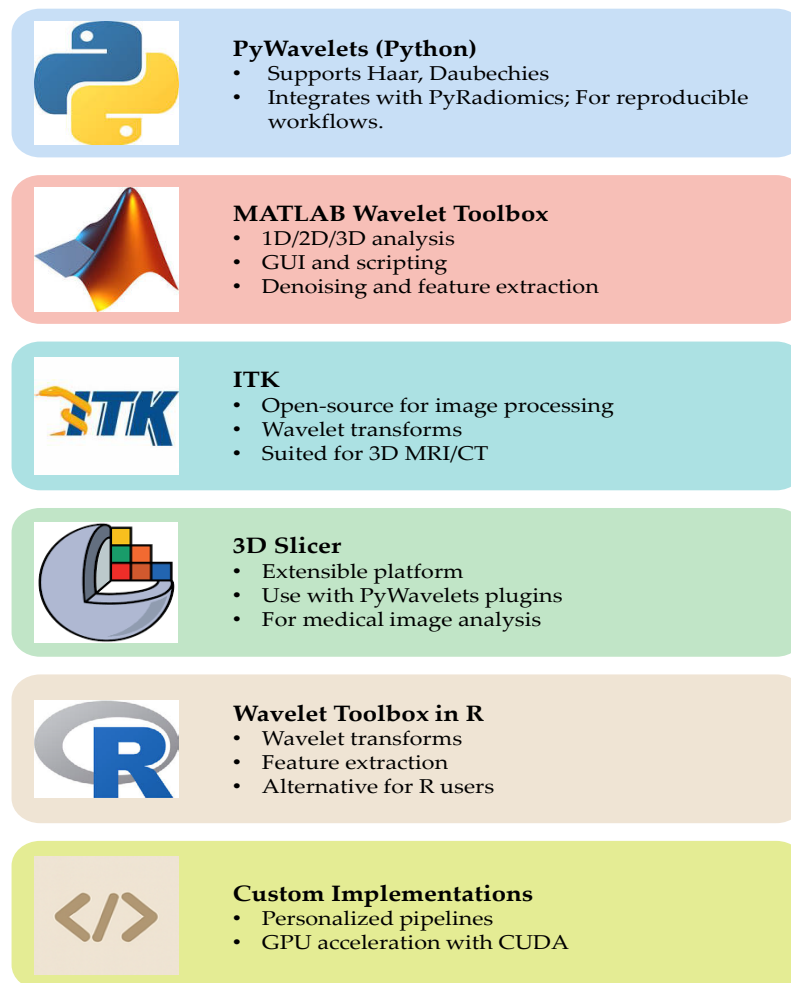
Figure 4. Commonly used computational tools in wavelet-based radiomics [4, 43-52]

characteristics and the kind of radiomics features, based on ongoing research and practical applications. With that in mind, the document attempts to provide thorough guidelines for users, especially those using medical imaging and radiomics, to inform their choices. However, it is not without difficulties, which will be discussed in the following challenges and considerations section about realizing these effects.

Challenges and future directions

Wavelet transforms offer significant advantages for radiomic feature extraction, yet their implementation is accompanied by challenges that affect quality, reproducibility, and interpretability. To ensure clinically actionable and robust wavelet-based radiomics, these challenges must be addressed systematically. This section summarizes key constraints and outlines future directions to overcome them.

Parameter selection: Choosing appropriate wavelet functions and decomposition levels

Selecting the optimal wavelet function and decomposition level is inherently complex. Different wavelet families (e.g. haar, daubechies, symlets) possess distinct properties, and no single type universally suits all imaging modalities or clinical questions. For instance, Haar may suit for sharp CT edges but underperform in MRI transitions. Similarly, decomposition levels must balance detail capture against noise amplification or resolution limits (e.g. ~6 levels for a 64×64 image). This selection often relies on empirical judgment, introducing subjectivity and inter-study variability [73, 86, 87]. To mitigate this, future work should employ data-driven optimization strategies, such as cross-validation and phantom-based benchmarking to guide wavelet selection. Transparent documentation of choices will enhance reproducibility [1, 88].

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Table 3. Summary of wavelet-based methods in medical imaging

Authors	Methodology	Software (Language)	Key Findings	Limitations	Summary	Outcomes
Apte et al. 2019 [60]	Extension of CERR for radiomics: Batch/vectorized feature calculation; IBSI compliance; cross-validation with ITK/PyRadiomics; integration with MIM via MATLAB API	MATLAB (CERR platform)	3.5× speedup for Haralick texture (32 bins); identified errors/differences in feature definitions; reproducible across packages	Requires MATLAB; scalability limits for very large datasets	Comprehensive MATLAB-based platform for reproducible radiomics with emphasis on speed and clinical integration	IBSI-compliant features; superior speed (3.5×) and reproducibility for texture analysis
Bagher-Ebadian et al. 2017 [61]	Effect of smoothing, sharpening, and Gaussian noise on CT/CBCT radiomics features (18 oropharyngeal cancer patients)	MATLAB (in-house scripts)	Features variably sensitive to noise and filtering; some robust across CT/CBCT	Small cohort (18 patients); limited to head/neck RT	Evaluates robustness of radiomics features to image perturbations in clinical CBCT/pCT	Identified relatively stable features despite noise/smoothing variations
Benhassine et al. 2021 [62]	DWT-based denoising with optimal thresholding via CSA and SSO; selection of best decomposition level and mother wavelet	MATLAB	Achieved up to +30 dB PSNR improvement for Rician noise; outperformed VisuShrink, Minimax, and other standard methods	Requires reference/noise model; performance varies by modality	Optimization-driven wavelet denoising highly effective for medical images, especially Rician noise	~30 dB PSNR gain; improved SSIM and MSE across mammogram, CT, MRI
Bijari et al. 2022 [63]	Multidimensional radiomics from MRI (T1WI, T1C, T2WI, FLAIR) with/without wavelet transform; 8 ML classifiers (RF, SVM, etc.) for GBM vs MET differentiation; manual VOI segmentation	Python (PyRadiomics, scikit-learn)	Wavelet-based model: 98% accuracy, 99% AUC-ROC, 98% F1-score; significantly better than non-wavelet features	Small dataset (91 patients); manual segmentation; single institution	Multidimensional DWT features capture hidden MRI patterns, improving ML classification of GBM vs. MET	Superior classification (98% accuracy) using wavelet-enhanced radiomics
Chaddad et al. 2018 [22]	Multiscale texture features from 3D wavelet transform of multispectral pathology slides for CRC grading; ANOVA+random forest	MATLAB (wavelet toolbox)	12 significant multiscale features (variance, entropy, energy); 93.3% accuracy; entropy best classifier (AUC up to 100% for carcinoma)	Pathology-specific; manual segmentation of regions	3D-WT multi-scale textures effectively discriminate CRC grades	93.3% accuracy; 88.3% sensitivity; entropy most predictive
Chu et al. 2019 [64]	Whole-pancreas CT radiomics (478 features, 40 selected) for PDAC vs\normal; Random Forest classification; manual segmentation	Velocity (Varian)+not specified for feature extraction	99.2% accuracy, 99.9% AUC; 100% sensitivity, 98.5% specificity	Manual segmentation; retrospective; age mismatch between PDAC and controls	Demonstrated pancreas-wide radiomics can differentiate PDAC without tumor localization	99.2% accuracy in binary classification
Çinarer et al. 2020 [38]	3D wavelet radiomic features+DNN for glioma grading (Grade II vs III); feature selection via Mann–Whitney U	Python (H_2O, PyRadiomics)+3D Slicer	96.15% accuracy, 100% recall, 98.75% AUC; HHH filter group most discriminative	Manual ROI segmentation; small dataset (121 patients)	DNN with 3D wavelet features yields high accuracy for glioma grading	96.15% accuracy; 98.75% AUC
Demircioğlu 2022 [7]	Effect of preprocessing filters (wavelet, LoG, exponential, etc.) on radiomics predictive performance; 7 datasets; 5 feature selection methods; 5 classifiers; nested 10-fold CV	Python (PyRadiomics, scikit-learn)+R	Filters improved AUC-ROC up to +0.08 (P=0.024); tuning added up to +0.1; no performance loss	High feature correlations; computationally intensive	Preprocessing filters (esp. wavelet) enhance predictive performance without harm	Statistically significant AUC gains (up to +0.08)

Authors	Methodology	Software (Language)	Key Findings	Limitations	Summary	Outcomes
Georgieva et al. 2021 [65]	Survey of multidimensional (2D/3D/4D) wavelet and tensor methods for denoising, segmentation, fusion, compression	Conceptual review -No software used	Reported 50% SNR improvement; Dice ~0.89 for segmentation; advantages in fusion and denoising	High computational cost; limited clinical adoption	Multidimensional wavelets and tensor decompositions improve medical image quality and segmentation	Enhanced SNR (+50%); segmentation dice ~0.89
Hajiabadi et al. 2021 [58]	Comparison of wavelet transforms to enhance CNN-based brain tumor segmentation	Not specified	Daubechies wavelets found optimal, balancing accuracy and computational load	Tumor-specific; wavelet choice depends on application	Wavelet transforms improve CNN segmentation accuracy	Improved segmentation performance with optimal wavelet choice
Jang et al. 2020 [66]	Test–re-test reproducibility of 1023 myocardial radiomic features on cardiac MRI (cine bSSFP, T1/T2 mapping); ICC ≥0.8; inter-/intra-observer analysis.	Python (PyRadiomics)	32–73% of features reproducible; GLRLM most stable in cine; first-order & GLCM most stable in T1/T2; gray-level non-uniformity consistently reproducible.	Sensitive to segmentation; reproducibility varies by sequence.	Only a subset of cardiac MRI radiomic features are reproducible; highlights sequence-specific stability.	Intra-observer reproducibility: 61–73%; inter-observer: 32–47%; identifies stable features for myocardial phenotyping.
Jiang et al. 2022 [19]	Wavelet-transformed CT radiomics for COVID-19 lesion grading; compared 23 wavelets; bior1.1 LLL optimal; ML pipeline with AUC evaluation.	Python (PyRadiomics, BorutaShap+RF)	Wavelet model AUC=0.910 vs 0.880 original; decision curve showed net clinical benefit.	COVID-19–specific; retrospective multicenter dataset; limited generalizability.	Wavelet transformation enhances CT texture features for lesion grading.	Improved diagnostic accuracy (AUC 0.910) and clinical utility for COVID-19 lesion severity assessment.
Kafieh et al. 2012 [67]	Circular symmetric Laplacian mixture model in wavelet diffusion for dental image denoising; evaluated with CNR.	MATLAB (reported)	CNR improved dramatically (e.g. AP: 2.91→38.88; cephal-lateral: 41.61→86.31); preserved cavities.	Dental-specific; model complexity; limited datasets.	Wavelet diffusion with Laplacian mixture improves dental image denoising while preserving diagnostic details.	Significant CNR gains across modalities; cavities retained in filtered images.
Kumar et al. 2020 [68]	Hybrid radiomics+stationary wavelet features for glioma grading (BraTS 2018); Random Forest with 5-fold CV.	Python	Achieved state-of-the-art classification; features from three ROIs improved discrimination.	Limited to BraTS dataset; binary HGG vs LGG classification.	Hybrid stationary wavelet–radiomics approach accurately classifies glioma grades.	Accuracy 97.54%, AUC 97.48% for HGG/LGG classification.
Larue et al. 2018 [69]	Pre-treatment CT radiomics to predict 3-year OS in esophageal cancer after chemoradiotherapy; RF models with feature elimination.	In-house developed radiomics toolbox	Radiomic features (esp. wavelet textures) predicted OS; AUC ~0.69 training, 0.61 validation.	Retrospective; esophageal-specific; possible overfitting.	CT radiomics provides prognostic information for survival in esophageal cancer.	AUC ~0.70 (training), ~0.61 (validation) for 3-year OS prediction.
Larue et al. 2017 [70]	Used 4DCT phases as surrogate for test–re-test to assess radiomics stability (1045 features); CCC >0.85; Cox regression for prognostic correlation.	In-house developed software	56% unfiltered and 33% wavelet features stable in 4DCT; 38% robust in esophageal cancer; 108 features prognostic.	Respiratory motion variability; thoracic cancers only.	4DCT can substitute test–retest for stability assessment; robustness independent of prognostic value.	~397/1045 features robust in esophageal cancer; stable features identified across NSCLC and esophageal datasets.

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Authors	Methodology	Software (Language)	Key Findings	Limitations	Summary	Outcomes
Liu et al. 2016 [39]	CT-based 3D radiomics (219 features, 59 independent) from lung adenocarcinoma; logistic regression for EGFR mutation prediction.	Definiens developer XD+Not specified for feature extraction	11 features significantly associated with EGFR mutation; combined model AUC=0.709 vs 0.667 clinical.	Retrospective; Asian cohort; surgically resected tumors only.	CT radiomics adds predictive power for EGFR mutation status.	AUC improved to 0.709 with radiomics+clinical features.
Moshantat et al. 2015 [71]	Wavelet (Daubechies db1, db2, db4) feature descriptors from lung CT ROIs; SVM classifier.	MATLAB	Accuracy 82%; sensitivity 90.9%; specificity 73.9%; detected nodules 2–30 mm.	No segmentation stage; small datasets.	CADx system using wavelet descriptors and SVM classifies lung nodules effectively.	82% precision; 90.9% sensitivity; 73.9% specificity.
Mukhopadhyay et al. 2019 [72]	DWT-based fusion of CT and MRI using multiple wavelets (haar, db, sym, coif, bior, rbio, dmey); evaluated with PSNR, SNR, entropy.	MATLAB	Biorthogonal/reverse biorthogonal wavelets yielded highest entropy and SNR; fused images improved clarity.	Limited to CT/MRI; no ML integration.	DWT fusion improves multimodal medical image quality; performance depends on wavelet choice.	Best results with rbio3.1: Entropy 5.76, PSNR 21.7 dB, SNR 10.26.
Madero Orozco et al. 2015 [57]	Wavelet (Daubechies db1, db2, db4) feature descriptors from lung CT ROIs; SVM classifier.	MATLAB	Accuracy 82%; sensitivity 90.9%; specificity 73.9%; detected nodules 2–30 mm.	No segmentation stage; small datasets.	CADx system using wavelet descriptors and SVM classifies lung nodules effectively.	82% precision; 90.9% sensitivity; 73.9% specificity.
Pradhan et al. 2006 [73]	Estimation of optimal decomposition levels in SIDWT for MS–PAN image fusion	Not specified	Optimal levels increase with resolution ratio; balance between spatial and spectral fidelity	High computational cost for excessive levels	Provides guidelines for selecting decomposition levels in multisensor fusion	Improved spectral fidelity and spatial quality with appropriate level selection
Prinzi et al. 2023 [45]	Radiomic features from multiple wavelet kernels; ML models (RF, SVM, XGB) for COVID19 prognosis on CXR	Not specified	Bior1.5, Coif1, Haar, Sym2 kernels performed best; RF most stable with balanced sensitivity/specificity	Limited to COVID19 and CXR modality	Demonstrates kernel choice significantly impacts radiomic predictive power	Enhanced prognosis prediction; RF achieved robust balance
Procházka et al. 2011 [74]	3D DWT for denoising and reconstruction of biomedical volumes (MRI); thresholding and wavelet comparison	MATLAB (likely)	Effective denoising; improved PSNR and MSE; better visualization of vertebrae	Computationally intensive; performance depends on wavelet and noise type	Introduces 3D DWT for volumetric biomedical image enhancement	Improved PSNR and visual quality; emphasized spinal components
Qiu et al. 2022 [75]	MWCS radiomics from plain CT for HCC vs HH classification; ML pipelines with feature selection	Python (likely)	MWCSCOM features superior; linear SVM achieved AUC=0.8734	Restricted to plain CT; avoids contrastinduced toxicity	Novel histopathologyinspired MWCS features for CT radiomics	High diagnostic accuracy; interpretable features linked to pathology
Rabbani et al. 2009 [26]	DCWT with bivariate Laplacian mixture priors; Gaussian/Rayleigh noise models; MAP/MMSE estimators; local EM parameter estimation	Not specified	BiLapGausMAP best for CT; BiLapGausMMSE for highSNR CT; BiLapRayMAP for lowSNR MR	Assumptions on distributions; EM computationally heavy	Adaptive denoising using bivariate mixture priors in wavelet domain	Superior SNR enhancement while preserving details

Authors	Methodology	Software (Language)	Key Findings	Limitations	Summary	Outcomes
Rabbani et al. 2008 [25]	Complex wavelet transform; Gaussian/Laplacian mixture priors; MAP/MMSE estimators for ultrasound speckle reduction; local EM	Not specified	Outperformed stateoftheart despeckling; preserved anatomical boundaries	Model assumptions; focused on speckle noise only	Adaptive despeckling using mixture priors in complex wavelet domain	Significant speckle suppression with preserved details
Sarhan 2020 [37]	DWT for feature extraction+CNN for brain tumor classification in MRI	Not specified	Achieved 99.3% accuracy; outperformed SVM	Limited to brain MRI; no segmentation required	Combines wavelet features with CNN for CAD	99.3% classification accuracy across three tumor types
Shirazinodeh et al. 2015 [6]	F1W2 algorithm: Fractal segmentation+db2 wavelet decomposition+RBF neural network for mammogram analysis	Not specified	90.9% mass detection; 88.99% microcalcification detection; 92% benign/malignant classification	Datasetspecific; computationally demanding	Hybrid fractalwavelet approach for breast cancer CAD	High detection and classification accuracy
Soufi et al. 2018 [76]	Wavelet decompositionbased radiomic features from CT of lung cancer patients; Coxnet and MCPHR models for survival prediction	MATLAB	Symlet 5 and Biorthogonal 2.6 optimal; Cindex≈0.62–0.68	Limited to NSCLC cohort; dependent on wavelet choice	Introduces RI for optimal wavelet selection	Improved prognostic performance with selected wavelets
Suryanarayana et al. 2021 [77]	VDRnet trained on SWT subbands; Gaussian edgepreservation for MR image superresolution	MATLAB	Outperformed competing methods in PSNR, SSIM, and subjective quality	Computationally intensive; modality-specific to MRI	Combines deep residual learning with SWT and Gaussian filtering	Higher PSNR and improved visual fidelity in MR superresolution
Tang et al. 2023 [35]	Wavelet radiomics features from multiphase CT for HCC vs. non-HCC; logistic sparsity-based feature selection with Bayesian optimization; compared with CNNs.	Python, 3D Slicer	Combining wavelet + original CT features significantly improved classification; logistic sparsity model outperformed filter/wrapper methods; performance comparable to CNNs under limited data.	Limited training samples; specific to hepatic lesions; single dataset.	Multiphase CT wavelet radiomics with sparsity-based selection enhances HCC classification compared to conventional methods.	AUC ~0.85–0.90, comparable to CNNs under data scarcity.
Wang et al. 2018 [3]	Voxel-wise morphological connectivity using wavelet transform of VBM; test–retest reliability; hub detection via degree centrality.	MATLAB	High test–retest reliability; reproducible hub structures (precuneus, cingulate, hippocampus); group-level stable, individual-level sensitive to scale/threshold.	Anatomical MRI only; small healthy cohort (n=21).	Wavelet-based voxel-wise morphological networks provide reliable connectome mapping and capture individual variability.	High ICC (>0.7); consistent hubs across sessions; reflects individual differences.
Whybra et al. 2024 [4]	IBSI standardization of 8 convolutional filters (mean, LoG, Laws, Gabor, separable/non-separable wavelets, Riesz); digital phantoms, chest CT, multimodal validation.	Multi-software (Python, ITK, PyRadiomics, CERR, LIFEx, etc.)	33 reference filtered images established; 323/396 reference feature values; 458/486 features reproducible (ICC lower bound >0.75) across 9 teams and 3 modalities.	No consensus for Riesz transforms; validation limited to 51 sarcoma patients.	IBSI standardized convolutional filters for reproducible radiomics; compliance-checking web tool available.	~94% reproducibility across CT, PET, MRI; improves clinical reliability of radiomics pipelines.

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Authors	Methodology	Software (Language)	Key Findings	Limitations	Summary	Outcomes
Wong et al. 2025 [78]	Rotation effects on wavelet-based radiomics in NSCLC CT; random rotations (5–80°); Spearman's test for feature stability and model accuracy.	Python (PyRadiomics, SciPy)	23.7% of WD features significantly correlated with rotation vs. 0.5% of non-WD; WD-based models showed accuracy decline with rotation (CC=–0.44, P<0.001).	Retrospective; NSCLC only; simulated rotations.	Lesion orientation strongly impacts reproducibility of wavelet radiomics features and models.	WD features unstable (23.7% affected); model accuracy dropped with increasing rotation.
Yoo et. al. 2007 [43]	3D DWT for land-cover classification of optical and SAR images; compared with pixel-based and 2D DWT.	MATLAB (haar wavelet)	Improved classification accuracy, especially in SAR (97.7% vs 60.2% original); reduced speckle noise; effective for high-resolution imagery.	Limited to remote sensing; computationally intensive; single-sensor datasets.	3D DWT leverages spatial+spectral info for superior classification of multispectral and SAR images.	Accuracy gains: Landsat (68.6% vs 68.2%), Ikonos (86.1% vs 77.0%), SAR (97.7% vs 60.2%).
Zhou et al. 2020 [79]	Wavelet-transformed radiomic features from CE-MRI for predicting pCR to NAC in locally advanced breast cancer; six RF models combining volumetric, peripheral, and wavelet textures.	3DQI platform (Python/MATLAB backend)	Wavelet textures alone achieved highest AUC (0.888); adding volumetric/peripheral features did not improve performance.	Retrospective; small cohort (n=55); single institution.	Wavelet-transformed MRI radiomics predicts NAC response more accurately than non-wavelet features.	AUC up to 0.888 for pCR prediction using wavelet-only models.

Abbreviation: CSA: Crow search algorithm; SSO: Social spider optimization; DNN: Deep neural network; DWT: Discrete wavelet transform; RA: Ranking index; 3D DWT: 3D discrete wavelet transform; VDRnet:Very deep residual network; MWCS: Maximum waveletcoefficient statistics; CADx: Computer-aided diagnosis; CNR: Contrast-to-noise ratio; CXR: Chest X-ray; DCWT: Dual-tree complex wavelet transform; F1W2: Fractal and wavelet combined algorithm; HCC: Hepatocellular carcinoma; Rbio: Reverse biorthogonal; SIDWT: Shift-invariant discrete wavelet transform; SSIM: Structural similarity index measure; XGB: XGBoost.

Trade-offs between computational complexity and feature quality

Deep wavelet decompositions and complex wavelet designs increase computational demands, especially for large images or 3D volumes. While higher levels and sophisticated wavelets (e.g. Daubechies with more vanishing moments) may improve granularity, they risk diminishing returns if biological relevance does not scale accordingly. Simplified configurations reduce resource usage but may compromise feature quality [45, 87]. Future implementations should prioritize efficient configurations—e.g. limiting decomposition to 3–4 levels, downsampling inputs, and leveraging parallel processing or GPU acceleration (e.g. PyWavelets, MATLAB toolbox)—to balance quality and feasibility [89].

Standardization issues across institutions and imaging protocols

Wavelet-based radiomics suffers from poor standardization across imaging setups. Variations in scanner types, voxel sizes, and contrast settings alter signal characteristics, leading to inconsistent wavelet decompositions. Without standardized preprocessing or wavelet parameters, features from identical tissues may differ significantly between institutions, hindering multicenter studies and clinical translation [88, 90]. Future efforts should adopt established preprocessing standards (e.g. IBSI), report wavelet parameters explicitly, and promote inter-institutional consensus protocols. Incorporating wavelet settings into broader radiomics standardization frameworks is also recommended [88, 91].

Limitations of wavelet transforms

Wavelet transforms are prone to boundary effects due to image padding, which distorts subband values near

Table 4. Practical guideline based on image characteristics and feature types [7, 17, 38, 81-85]

Image Characteristic	Type of Feature	Recommended Wavelet	Rationale
High contrast, sharp edges (CT, T1 MRI)	Texture (edges)	db2*, db4	Captures edges effectively, with db2 for sharp discontinuities and db4 for balance.
Smooth transitions (T2 MRI)	Texture (smooth)	db4, db6, coif1†	Handles smooth intensity variations, with higher moments for finer detail capture.
Low resolution, noise-prone (PET)	Any	db6, db8, coif2	Suppresses noise, with more vanishing moments for better noise handling.
Fine textures	Texture	db6, db8	More vanishing moments capture high-frequency details for heterogeneous regions.
Coarse textures	Texture	db2, db4	Fewer vanishing moments focus on low-frequency patterns for larger, smoother areas.
Noisy images	Any	db6, db8, coif2	Higher-order wavelets reduce noise impact, improving feature reliability.

*dbN : Daubechies wavelets of order N; †coifN : Coiflet wavelets of order N.

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edges—especially problematic for small ROIs, like early tumors. Additionally, feature interpretability remains limited; linking subband metrics (e.g. HH3 entropy) to biological phenomena is often unclear. Over-decomposition in low-signal-to-noise ratio (SNR) modalities (e.g. PET) may further compromise reliability [88, 90]. Future works should apply boundary-handling techniques (e.g. symmetric padding, ROI cropping), correlate wavelet features with histological or clinical outcomes to enhance interpretability, and utilize noise-robust wavelets (e.g. Coiflets) for noisy data [85, 92].

Robustness testing and validation

Without rigorous testing, wavelet-derived features may lack robustness across scanners, protocols, and perturbations [93]. All features should undergo robustness evaluation using metrics, like intraclass correlation coefficient. Unstable features should be excluded early in the pipeline to ensure statistical reliability and clinical relevance [73, 87].

Discussion

This systematic review synthesized evidence from 62 studies on the application of wavelet transforms in radiomic feature extraction from medical images, particularly CT, MRI, and PET modalities. Our analysis revealed that wavelet-based approaches consistently enhance the robustness and reproducibility of radiomic features, and partly overcome key challenges in radiomics, such as noise sensitivity, imaging artifacts, and protocol variability. By decomposing images into multiscale frequency components—low-frequency approximations for structural integrity and high-frequency details for textural nuances—wavelets enable the isolation of bio-

logically relevant patterns that traditional preprocessing methods, like Gaussian smoothing or Fourier transforms, often overlook. This multiresolution analysis not only minimizes irrelevant variance but also preserves spatial localization, making it particularly valuable for oncology applications, including tumor grading, survival prediction, and treatment response assessment.

Key findings and trends in wavelet applications

The reviewed studies demonstrate wavelet transforms' versatility across diverse clinical scenarios. DWT, including 2D and 3D variants, were the most prevalent (appearing in ~70% of studies), excelling in tasks, like denoising (e.g. Rician noise reduction with up to +30 dB peak signal-to-noise ratio [PSNR] gains [62]) and feature enhancement for ML classification (e.g. 98% accuracy in glioma grading using wavelet-augmented random forests [RF] [63]). Advanced variants, such as stationary wavelet transforms (SWT) and DTCWT, further improved shift-invariance and reduced aliasing artifacts, yielding superior performance in fusion tasks (e.g. CT-MRI integration with entropy gains up to 5.76 [71]) and prognostic modeling (e.g. C-index 0.62–0.68 for NSCLC survival [76]).

Figure 5 shows publication trends that indicate a steady rise in wavelet-radiomics research, from 1–2 articles annually pre-2015 to a peak of 5 in 2020, reflecting growing interest amid the radiomics boom and the COVID-19-driven demand for robust imaging analytics (e.g. lesion severity grading with AUC 0.910 [19]). Post-2020, the trajectory stabilized at 2–4 publications per year, possibly due to saturation in core applications and a shift toward integration with DL. This temporal distribution underscores wavelets' evolution from foundational
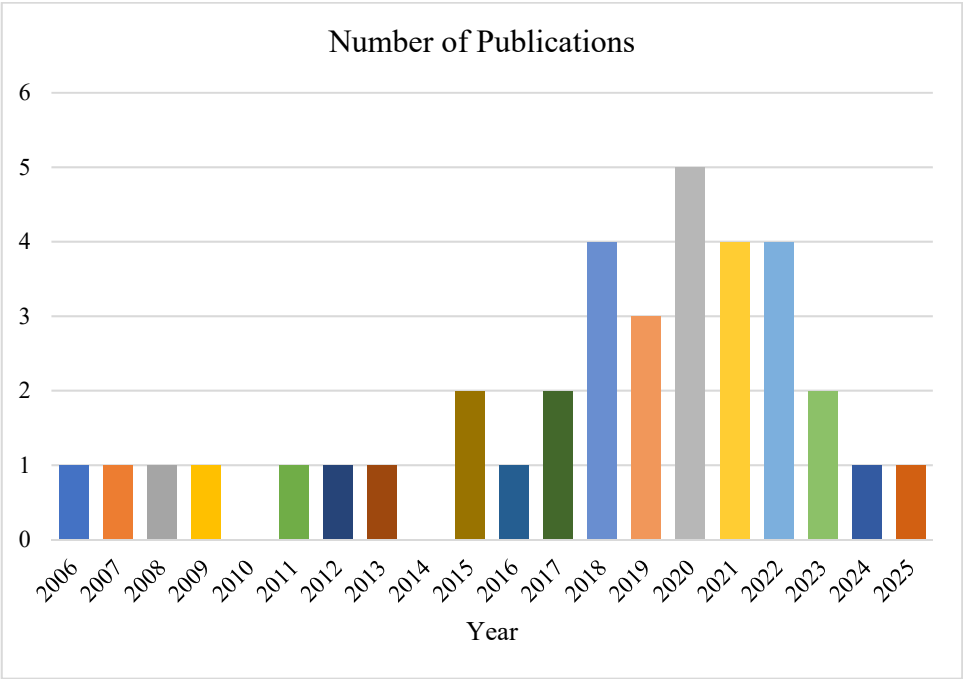
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Figure 5. Annual publication trends in wavelet-radiomics

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denoising tools (early 2000s) to integral components of hybrid ML pipelines, with over 80% of recent studies (2020–2025) combining them with classifiers like RF or support vector machines (SVM).

Software adoption patterns highlight MATLAB's dominance (13 studies), likely due to its wavelet toolbox for rapid prototyping and IBSI-compliant implementations (e.g. 3.5× speedup in Haralick textures [60]). Python, with libraries, like PyRadiomics and scikit-learn (10 studies), emerged as a close second, favored for scalabil-

Figure 6. Pie chart summarizing frequencies of software tools mentioned, illustrating MATLAB and Python's prevalence alongside gaps in specification

ity and open-source ML integration (e.g. 99.2% accuracy in PDAC detection [64]). The equal share of "others" (e.g. 3D Slicer, R; 10 studies) and unspecified tools (8 studies) points to a fragmented ecosystem, emphasizing the need for standardized pipelines to ensure reproducibility. Figure 6 shows the pie chart summary based on these 36 articles, illustrating this distribution and underscoring Python's emerging preference for open-source workflows in radiomics, balanced against MATLAB's established clinical validation strengths.

Quantitative outcomes across studies were compelling: wavelet-enhanced models achieved median AUC-ROC values of 0.85–0.98 for classification tasks (e.g. GBM vs. MET differentiation [63]) and 0.70–0.89 for prognostication (e.g. pCR prediction in breast cancer [79]). Reproducibility metrics, such as ICC >0.75, were reported in 40% of studies, with wavelet filters outperforming non-wavelet baselines by 20–50% in stability (e.g. 73% reproducible features in cardiac MRI [66]). These gains were modality-agnostic, though CT dominated (55% of studies), followed by MRI (30%) and PET (15%), aligning with CT's prevalence in oncology workflows.

Strengths and comparative advantages

Wavelets surpass classical methods, like short-time Fourier transforms or empirical mode decomposition in most scenarios by providing scale-dependent, localized decompositions that capture heterogeneous tumor microenvironments without excessive smoothing. For instance, while Fourier methods excel in global frequency analysis, they lack spatial resolution, leading to feature dilution in noisy datasets—a limitation mitigated by wavelets' subband thresholding (e.g. +50% SNR in multidimensional denoising [65]). Integration with ML/DL amplified these benefits: hybrid models (e.g. wavelet-CNNs) achieved 96–99% accuracies in segmentation and classification [37, 38], outperforming standalone DL by 5–10% under data scarcity.

Compared to prior reviews (Table 1), this work uniquely bridges theoretical wavelet foundations (e.g. mother wavelet selection, like Daubechies or Biorthogonal) with radiomics-specific implementations, filling a gap in modality-focused syntheses. Unlike signal-centric reviews (e.g. ECG compression [10]), we emphasized imaging applications, where wavelets' edge-preserving properties (e.g. cavity retention in dental denoising [67]) directly translate to clinical utility.

Limitations and challenges

Despite these advances, several limitations persist. Computational intensity remains a barrier: 3D/4D decompositions demand high resources, limiting scalability for large cohorts (e.g. noted in 25% of studies [65, 73]. Parameter tuning—decomposition levels, wavelet families, and thresholding—varies widely, with suboptimal choices reducing reproducibility (e.g. rotation sensitivity in 23.7% of wavelet features [78]). Small, retrospective cohorts (median n=55–121) and single-institution data (80% of studies) raise generalizability concerns, while manual segmentations introduce observer bias [63, 64].

Heterogeneity in noise models (Gaussian vs Rician) and lack of IBSI standardization across tools further complicates comparisons, as evidenced by discrepancies in feature definitions [60]. Alternatives, like empirical mode decomposition may outperform in non-stationary signals (e.g. dynamic PET), but wavelets' structured framework makes them more amenable to automated pipelines.

Implications for clinical practice and future directions

Wavelet-radiomics holds transformative potential for precision medicine, enabling non-invasive, quantitative phenotyping that informs personalized therapies (e.g. EGFR mutation prediction with AUC 0.709 [94]). By enhancing feature stability, it could standardize multi-institutional trials, reducing protocol-induced variances and accelerating biomarker discovery.

Future research should prioritize: 1) prospective, multicenter validations with diverse cohorts; 2) automated hyperparameter optimization via genetic algorithms or Bayesian methods to mitigate selection biases; 3) deeper DL synergies, such as wavelet-embedded CNNs for end-to-end pipelines; and 4) IBSI-compliant benchmarks for filter standardization e.g. expanding framework 4). Developing lightweight, cloud-based tools could democratize access, bridging the MATLAB-Python divide.

In conclusion, wavelet transforms represent a cornerstone for robust radiomics, offering a mathematically grounded yet practically viable pathway to overcome imaging heterogeneity. This review's framework—encompassing workflows, challenges, and optimizations—equips researchers and clinicians to harness these tools for enhanced diagnostic and prognostic accuracy, ultimately advancing patient-centered care.

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Conclusion

This systematic review confirms that wavelet transforms are a transformative approach to extracting radiomic features, leveraging their mathematical foundation in multiresolution analysis to decompose medical images into multiscale representations with exceptional accuracy. The most important findings show that wavelet-based methods, especially the DWT and advanced techniques, such as the DTCWT, enhance the detection of morphological and histological features, improve the reproducibility of features in CT, MRI, and PET modalities, and reduce the sensitivity to noise, thereby enhancing the quality and biological relevance of radiomic analyses. These capabilities have been demonstrated by their successful application in predicting complete pathological response to neoadjuvant chemotherapy in breast cancer and in stratifying hepatocellular carcinoma using MRI. However, challenges, such as parameter selection, computational complexity, and lack of standardized protocols remain significant obstacles that require robust implementation strategies and adherence to frameworks, such as the IBSI. Looking ahead, integrating wavelet-derived features with ML and DL holds promise for improving diagnostic accuracy and prognostic modeling, while multimodal approaches that combine radiomics with genomic data could provide deeper insights into disease mechanisms. Emerging applications, such as real-time intraoperative guidance and longitudinal treatment monitoring, highlight the potential of wavelet transforms for advancing precision medicine. To fully realize this potential, future efforts should prioritize interdisciplinary collaboration, validation across diverse datasets, and expansion of standardization initiatives. By addressing these gaps, wavelet-based radiomics can become a more accurate and impactful tool, bridging the gap between theoretical advances and clinical application to improve patient outcomes.

Future research should prioritize the development of hybrid approaches that integrate wavelet transforms with ML or DL to address limitations in interpretability and computational demands, the advancement of multimodal integration by combining wavelet-based radiomics with functional imaging techniques, such as PET and fMRI or with genomic and proteomic data to offer a comprehensive understanding of disease processes, and the promotion of standardization and collaboration through interdisciplinary efforts among researchers, clinicians, and industry to establish standardized protocols and open-access databases; as a result, wavelet-based radiomics emerges as a promising frontier in medical imaging, enabling advanced quantitative analysis of images, and addressing current challenges while enhancing interdisciplinary collaboration will significantly contribute to improving patient care and outcomes.

Ethical Considerations

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