Application of Wavelet Transformation and Artificial Intelligence Techniques in Healthcare: A Systemic Review

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Application of Wavelet Transformation and Artificial Intelligence Techniques in Healthcare: A Systemic Review

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Received: 2 February 2024 | **Revised:** 18 December 2024 | **Accepted:** 25 February 2025

Associate Editor: Justin Wang | **Editor-in-Chief:** Witold Pedrycz

Funding: The authors received no specific funding for this work.

Keywords: artificial intelligence | healthcare applications | physiological signals | signal processing | wavelet transform

ABSTRACT

The integration of wavelet transformation and artificial intelligence techniques has demonstrated significant potential in healthcare applications. Wavelet analysis enables multi-scale signal decomposition and feature extraction that, when combined with machine and deep learning approaches, enhance the accuracy and efficiency of medical data analysis. This systematic review synthesizes 112 relevant studies from 2013 to 2023 exploring wavelet-based artificial intelligence in healthcare. Our analysis reveals that the discrete wavelet transform dominates (43% of studies), primarily used for feature extraction from biosignals (82%) and medical images. Major applications include cardiac abnormality detection (29%), neurological disorder diagnosis (27%), and mental health assessment (16%), with classification accuracies frequently exceeding 95%. Key findings indicate a shift from traditional machine learning to deep learning approaches after 2020, with emerging trends in hybrid architectures. The review identifies critical challenges in computational efficiency, optimal wavelet selection, and clinical validation. Future developments should focus on real-time processing optimization, interpretable deep learning models, multi-modal data fusion, and validation on larger clinical datasets, advancing the translation of these systems into practical clinical tools.

1 | Introduction

The healthcare industry is undergoing a significant transformation driven by challenges such as rising healthcare costs and a shortage of healthcare professionals. To address these issues, healthcare institutions are increasingly turning to information technology-based solutions and processes. Artificial intelligence (AI) has emerged as a powerful tool in healthcare, offering the potential to revolutionize patient care, disease detection, and medical research (Salvi et al. 2019, 2021). Alongside AI, the concept of wavelet transform (WT) has gained prominence in healthcare applications.

When dealing with patient care and disease detection, the concept of WT often comes into play due to its ability to analyze signals and images at different frequencies and resolutions. WT provides a powerful mathematical framework for decomposing signals into various frequency components, allowing for a more detailed analysis of the underlying data (Acharya et al. 2015). In the context of healthcare, this can help uncover hidden patterns, identify anomalies, and extract relevant features from medical data (Faust et al. 2015).

The combination of WT and AI enhances the accuracy, efficiency, and speed of data analysis, leading to better patient care, early disease detection, and improved medical research. However, it is important to note that the specific applications may vary depending on the healthcare institution and the nature of the medical data being analyzed.

This review paper aims to provide a comprehensive overview of the current WT approaches within the AI framework used in the healthcare domain. The primary objectives of this review are as follows:

- Explore and analyze the various WT techniques employed in healthcare applications within an AI context. This includes examining the different types of WTs, such as orthogonal WTs, CWTs, and higher-order WTs.
- Summarize key applications where WT is applied in healthcare. This review will explore various healthcare sectors, including medical imaging, EEG analysis, cardiovascular monitoring, and disease diagnosis.
- Outline the key benefits of applying WT within the AI context. This includes discussing how the combination of WT and AI enhances the accuracy, efficiency, and speed of data analysis, leading to improved patient care, early disease detection, and enhanced medical research capabilities.
- Discuss the limitations of current WT approaches and outline directions for future work. This review will critically assess the challenges and constraints faced in implementing WT techniques in healthcare applications. Additionally, it will identify research gaps and propose potential avenues for future investigations, such as exploring novel WT algorithms and optimizing computational efficiency.

To achieve these objectives, this review synthesizes insights from 112 relevant primary studies published between 2013 and 2023. By analyzing a wide range of literature, this review provides a comprehensive and up-to-date perspective on the integration of WT and AI in healthcare. The findings and discussions presented in this review paper intend to serve as a valuable reference for readers, enabling them to appreciate the progress made in this field, select suitable methods for their specific needs, and identify promising directions for further research and development.

2 | Methods

We closely adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to select the most relevant articles on multi-modality in healthcare.

2.1 | Related Reviews

The integration of WT with AI is highly relevant in the field of healthcare, and 5 recent reviews have been published in this area. However, these reviews have certain limitations in terms of their scope and focus:

- Abdulazeez et al. (2020) "The Applications of Discrete Wavelet Transform in Image Processing: A Review": This review discusses the use of DWT in various image processing tasks, including compression, reduction, optimization, and watermarking. The main limitation of this review is that it focuses on image processing applications and does not cover the broader scope of wavelet transformation in healthcare within an AI context.
- Grobbelaar et al. (2022) "A Survey on Denoising Techniques of Electroencephalogram Signals Using WT": The paper focuses specifically on the application of WT for denoising EEG signals. This paper provides a comprehensive overview of the survey findings in this area. However, it only focuses on denoising techniques for EEG signal processing.
- Guo, Zhang, et al. (2022) "A Review of Wavelet Analysis and Its Applications: Challenges and Opportunities": This review explores the developmental history of wavelet theory and delves into various wavelet properties. The paper extensively discusses the main models and algorithms of WT, with a primary focus on its application in signal processing. The authors exclusively focused on WT applied to signal processing, without delving into its applications in image-based contexts."
- Sabarimalai Sur and Dandapat (2014) "Wavelet-based electrocardiogram signal compression methods and their performances: A prospective review": This paper presents wavelet-based ECG compression methods and their performances. The primary limitation of this work stems from its narrow scope, as it does not encompass other signals or images within the healthcare field.
- Serhal et al. (2021) "Overview on prediction, detection, and classification of atrial fibrillation using wavelets and AI on ECG": This review provides an overview of various AI models employed in analyzing atrial fibrillation through WT. However, the authors do not include other biosignals or imaging modalities that could benefit from WT.

The objective of our review is to provide a comprehensive overview of WT and AI techniques in healthcare, addressing both biosignals and image applications. We will provide insights into the types of data used in conjunction with different types of WT. In addition to presenting the current landscape of WT and AI approaches in healthcare, this work will also address the benefits and challenges associated with their integration, suggesting potential solutions and avenues for future development. Figure 1 illustrates the comparison between our review paper and the previous literature reviews.

FIGURE 1 | Comparison of our review paper with existing literature reviews.

2.2 | Literature Search Strategy

This review focuses on articles published between 2013 and 2023 investigating the use of machine learning (ML) and deep learning (DL) methods for medical image analysis. A literature search was conducted in October 2023 across scientific databases including PubMed, IEEE Xplore, and Web of Science. The search strategy employed a Boolean approach, combining various keywords such as "Artificial Intelligence," "Machine learning," "Deep learning," "Healthcare," "Clinical," "Classification," "Detection," "Prediction," with "CT," "MRI," "PET," "X-ray," "ECG," "EMG," "EEG," "PPG," "EOG," "Fundus" in different combinations.

PRISMA guideline (Page et al. 2021) was used to filter our search results systematically, and 112 scientific articles were qualified for our review study. The initial search returned 552 articles. Articles were then screened to remove duplicates ($n=147$), as well as books, abstracts, and conference proceedings ($n=179$). The assessment of the studies was based on the following criteria:

i. The articles described the application of WT for data classification, detection, or prediction.
ii. The articles described methods based on ML or DL models.
iii. The articles were published in peer-reviewed journals.
iv. The articles were written in English.

Articles that did not meet these criteria were excluded, as well as pilot studies, works published before 2013, or articles not available in full text. The remaining studies ($n=226$) were further assessed based on journal quality, focusing on those published in top-quartile (Q1) journals according to impact factor metrics. This process resulted in a final set of 112 studies focusing on the application of WT and AI in healthcare that were included in this review. Figure 2 showcases the utilization of the PRISMA guideline for article selection.

2.3 | Types of WTs

In this section, we will discuss the major categories of WTs used in healthcare applications (Figure 3a). WTs are essential tools for signal processing, particularly in healthcare applications, as they decompose signals and images into frequency components. The choice of transform depends on the application's needs, with major categories including discrete, continuous, advanced time-frequency, stationary, and wavelet-based models.

The discrete wavelet transform (DWT) decomposes signals into frequency bands using discrete wavelet functions, offering good time-frequency localization. It is widely used for signal denoising, compression, and feature extraction.

The continuous wavelet transform (CWT) provides continuous time-frequency representations of signals. Variants like the Tunable Q-Factor Wavelet Transform (TQWT) allow control over the trade-off between time and frequency resolution. The Complex Continuous Wavelet Transform (CCWT) captures phase information, which is useful for signals with non-linear dynamics. The Flexible Analytic Wavelet Transform (FAWT) separates the real and imaginary parts of the coefficients for analyzing signals with time-varying phase or amplitude.

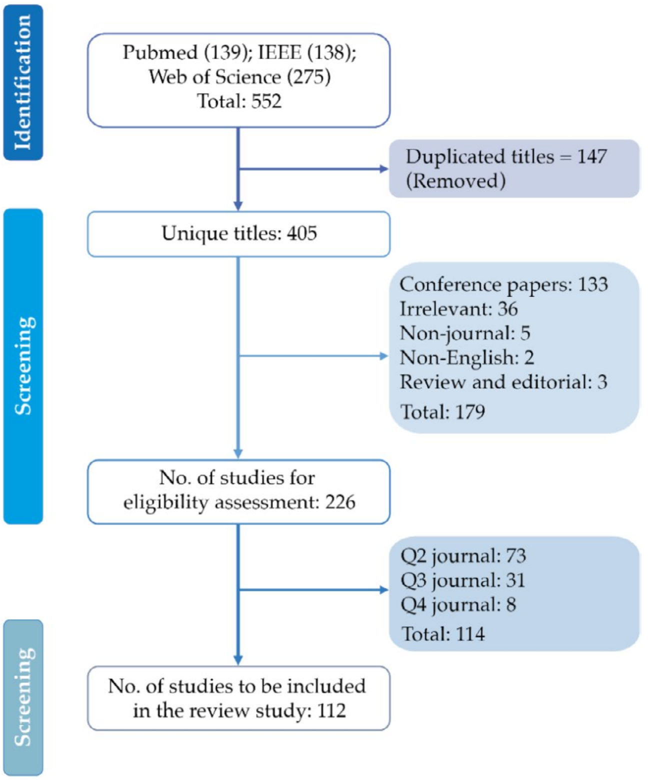

FIGURE 2 | Selection of relevant articles based on PRISMA guidelines.

Advanced Time-Frequency Transforms include the Cross-Wavelet Transform, which analyzes relationships between two signals, and the Frequency Slice Wavelet Transform (FSWT), which provides efficient computation at specific frequencies and is ideal for nonstationary signals.

The Stationary Wavelet Transform (SWT) is a translation-invariant method, providing robust signal representation unaffected by shifts. It is particularly useful for texture analysis and feature extraction from images.

Finally, Wavelet-Based Models combine wavelets with other techniques. The wavelet scattering transform (WST) offers a multi-scale, translation-invariant representation for classification and analysis. The empirical wavelet transform (EWT) adapts to varying spectral content in nonstationary signals, while the Wavelet Neural Network (WNN) integrates wavelets with neural networks for predictive modeling and pattern recognition.

2.4 | Healthcare Applications

In our study, we categorized AI and ML approaches based on the type of medical data integrated:

- *Biosignals*: Approaches integrating physiological monitoring signals, such as merging measurements from electrophysiological sensors, for example, Photoplethysmography (PPG), Electroencephalography (EEG), and Electrocardiography (ECG).
- *Bioimaging*: Approaches that fuse different medical image modalities, such as combining functional images (e.g., Positron Emission Tomography [PET]) with anatomical images (e.g., Computed Tomography [CT], Magnetic Resonance Imaging [MRI]).

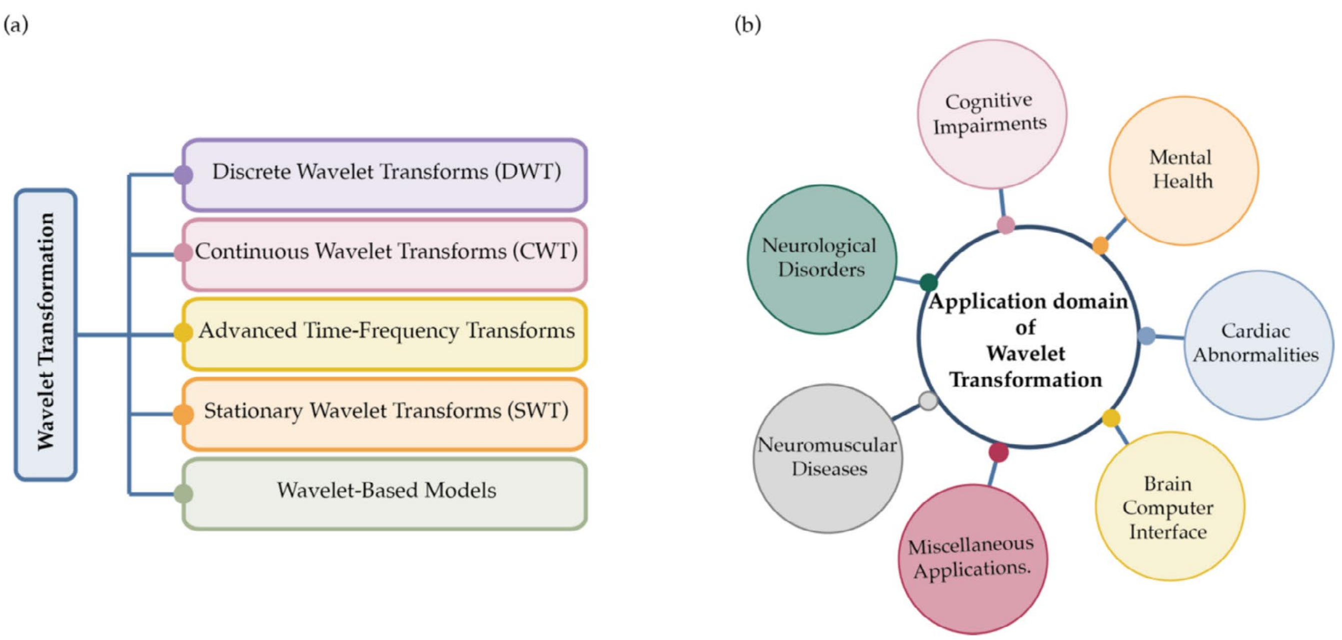

FIGURE 3 | (a) Major categories of wavelet transform used in healthcare applications. (b) Healthcare applications of wavelet transform.

These categories cover the most common data sources in healthcare: anatomical, functional, and biosignals data. The specific modalities used depend on the clinical question and available patient data. Additionally, we classified approaches by their application domain (Figure 3b). Eight domains were identified: cardiac abnormalities, mental health, cognitive impairments, neurological disorders, respiratory disorders, neuromuscular diseases, signal denoising, and miscellaneous applications. This secondary categorization by clinical area provides context on the intended patient populations and healthcare challenges each approach aims to address.

3 | Results

3.1 | Cardiac Abnormalities

Cardiac abnormalities encompass a wide range of conditions affecting the heart's structure and function, posing a significant global health challenge. WTs have demonstrated considerable potential in various stages of cardiac analysis, including signal decomposition, denoising, feature extraction, and the conversion of cardiac signals into time-frequency domain images. Table A1 and Figure 4 summarize the works reported in this section, the data type used, and the results obtained. Most of the works that employ WT to study cardiac abnormalities work on ECG data.

In ML applications, WTs are widely used for signal decomposition into frequency sub-bands. For instance, Giri et al. (2013) applied DWT to decompose heart rate variability (HRV) signals into sub-bands for the classification of coronary artery disease. Similarly, Martis et al. (2014) utilized DWT for decomposing ECG signals into frequency sub-bands, followed by dimensionality reduction and classification of five types of ECG beats. In another study, Martis, Acharya, Lim, et al. (2013) employed DWT for feature extraction from decomposed ECG signals to detect normal versus abnormal rhythms. Venkatesan et al. (2018) also used DWT to decompose ECG signals for HRV analysis and arrhythmia classification, while Tuncer et al. (2019) decomposed ECG signals using multiple DWT levels and applied local pattern techniques for classifying 17 arrhythmia classes.

WTs are also commonly applied for denoising ECG signals. Martis, Acharya, and Min (2013) used wavelet denoising to remove high-frequency noise from ECG signals before extracting cumulant features for cardiac abnormality classification. Elhaj et al. (2016) employed DWT for ECG denoising in the preprocessing stage, followed by feature extraction and dimensionality reduction with principal component analysis (PCA) for arrhythmia recognition. Similarly, Mohamed Suhail and Abdul Razak (2022) used DWT for preprocessing to eliminate noise and artifacts from ECG signals before applying ML for cardiac disease detection.

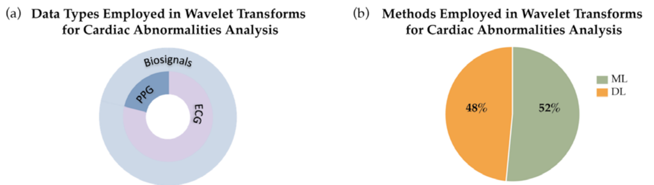

FIGURE 4 | Summary of the studies ($n = 36$) on wavelet and AI applied in cardiac abnormalities. (a) Sunburst diagram (outer ring: biosignals/images), inner ring: data used; (b) pie-chart ML versus DL approaches.

In addition to signal decomposition and denoising, WTs are also widely used for feature extraction, both linear and nonlinear. For instance, Gutiérrez-Gnecchi et al. (2017) employed wavelet coefficients extracted via DWT for arrhythmia classification, followed by dimensionality reduction with PCA to capture linear features. Sengupta et al. (2018) used DWT to extract features from ECG signals for predicting abnormal myocardial relaxation, feeding into a random forest (RF) classifier. Nonlinear feature extraction techniques have also been explored, such as in the work by Bashar, Han, et al. (2021), who applied DWT coefficients to calculate entropy and energy features for detecting premature atrial/ventricular contractions. In another study, Bashar, Ding, et al. (2021) used TQWT to extract time-frequency features like energy and spectral entropy for predicting atrial fibrillation in sepsis patients. Jothiramalingam et al. (2021) employed CWT to extract features from multi-lead ECG signals for detecting left ventricular hypertrophy (LVH) using ML techniques. Finally, Zeng, Yuan, et al. (2023) used TQWT to extract features from ECG signals, which were then classified using Convolutional Neural Network—Long Short-Term Memory (CNN-LSTM) networks for arrhythmia detection, demonstrating the versatility of wavelets in both linear and nonlinear feature extraction. Adam et al. (2018) proposed a method to distinguish normal ECG signals from myocardial infarction by decomposing the signals into frequency sub-bands using five-level DWT. Nonlinear features are then extracted from the DWT coefficients for classification.

Recently, WTs have been combined with DL models for ECG analysis, particularly for transforming 1D signals into 2D time-frequency images. Ma et al. (2021) used FSWT to convert ECG signals into 2D images, which were then input into a CNN for feature extraction and combined with an SVM classifier for improved atrial fibrillation detection. Xia et al. (2018) employed SWT and short-term Fourier transforms to create 2D matrices from ECG segments for deep CNN analysis, eliminating the need for P or R peak detection. Radhakrishnan et al. (2021) used Chirplet transform to generate time-frequency representations of ECG signals, which were input into a 2D Convolutional Neural Network—Bidirectional Long Short-Term Memory (2D CNN-BiLSTM) model for atrial fibrillation detection. Zhang et al. (2021) proposed generating 2D texture images from ECG signals, which were used as inputs to an Inception-ResNet-v2 CNN for classifying arrhythmias.

For signal decomposition, Panda et al. (2020) applied a fixed frequency range EWT filter bank to decompose ECG signals into different modes, which were then used as input to a deep CNN for detecting shockable ventricular arrhythmias. Similarly, Zeng, Su, Chen, and Yuan (2023) employed TQWT to decompose ECG signals into sub-bands for the classification of heart valve disorders using CNN networks. In terms of feature extraction, Houssein et al. (2022) and Li et al. (2022) used DWT as part of the feature extraction process for arrhythmia classification, feeding the extracted features into CNN models. Kim et al. (2023) also applied DWT for feature extraction in

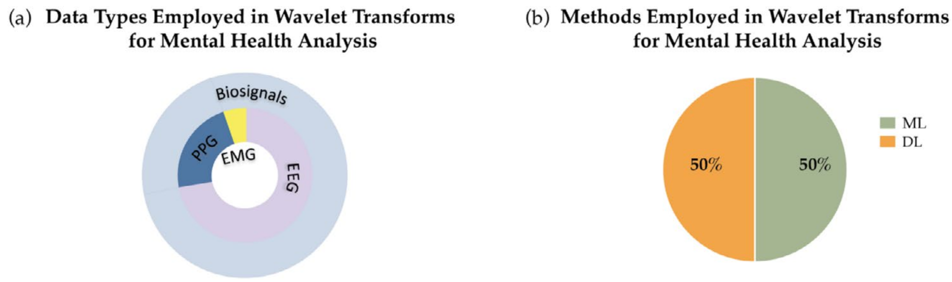

FIGURE 5 | Summary of the studies ($n = 18$) on wavelet and AI applied in mental health. (a) Sunburst diagram (outer ring: biosignals/images), inner ring: data used; (b) pie-chart ML versus DL approaches.

a real-time system designed to detect the R peak and classify arrhythmias on an embedded system. Peng et al. (2022) used DWT for preprocessing to denoise ECG signals, enhancing the feature extraction process for classification tasks. Chatterjee et al. (2022) proposed a hybrid ECG denoising technique that combines sparse optimization and WT, followed by thresholding and classification with an extreme learning machine-based autoencoder. Poungponsri and Yu (2013) also utilized DWT for ECG signal denoising, decomposing signals into coefficients which were then processed by neural networks for noise reduction. Karri and Annavarapu (2023) also used DWT for both noise reduction and feature extraction in their arrhythmia classification model, which was then followed by classification using a neural network.

Several studies have applied WT to analyze phonocardiography (PCG) signals for detecting cardiac anomalies. Zeng, Su, Chen, and Yuan (2023) extracted features from PCG signals using TQWT and classified heart valve disorders using CNN networks. Additionally, WTs are widely used for denoising ECG signals. Sawant et al. (2021) used Fano-factor constrained tunable quality wavelet transform (FWT) to decompose heart sound signals into sub-bands for binary classification. Zeng et al. (2021) employed TQWT and variational mode decomposition (VMD) to detect abnormal heart sounds, extracting features from the sub-band with the highest energy. Bhardwaj et al. (Bhardwaj et al. 2023) used CWT to obtain time-frequency scalograms of PCG signals for classifying valvular heart diseases with deep CNNs. Rajeshwari et al. (2023) applied CWT and the Teager–Kaiser energy operator to segment heart sound events, such as systolic clicks and murmurs, for detecting mitral valve prolapse. Shuvo et al. (2023) introduced NRC-Net, a convolutional recurrent neural network (CRNN) for classifying heart conditions from noisy PCG signals, using CWT to transform heart sounds into images. Dhar et al. (2021) utilized cross-WT to create time-frequency spectra of PCG signals for classification using the AlexNet CNN model. Finally, Zeng, Su, Yuan, and Chen (2023) employed TQWT to decompose PCG signals into sub-bands, selecting the one with the highest energy for classification.

This section highlights how WTs have proven highly effective for signal decomposition, denoising, and feature extraction in cardiac signal analysis, enabling more accurate detection and classification of various cardiac conditions. Ahmed et al. (2023) developed a hybrid method for denoising PPG signals using DL and fast WT, where the noisy signal is decomposed, and the clean signal is reconstructed using a deep neural network.

3.2 | Mental Health

Mental health is a critical aspect of overall well-being, encompassing our emotional, psychological, and social well-being. Figure 5 and Table A2 summarize the works reported in this section, along with the data type used and the results obtained.

In mental health research, EEG signals are commonly used for studying various conditions, with WTs playing a crucial role in feature extraction for ML classification. Studies such as Kumar Upadhyay and Nagpal (2020) and Tuncer et al. (2021) applied WT to decompose EEG signals into frequency sub-bands, extracting statistical, power, and fractal features for the classification of stress, sleep stages, and emotions using classifiers like support vector machine (SVM) and radial basis function neural network (RBFNN). Gosala et al. (2023) compared different WT methods (CWT, DWT, WST) for detecting schizophrenia, achieving high accuracy with CWT features. Pant et al. (Pant et al. 2022) applied FAWT for feature extraction from ECG signals to detect sleep apnea, using an ensemble classifier for accurate classification. Other studies, like Tor et al. (2021) and Sharma et al. (2022), also employed WT to extract nonlinear features for the classification of attention deficit hyperactivity disorder (ADHD) and stress, showcasing the versatility of WT in mental health applications. Richmond et al. (2021) introduced a system for detecting sleep apnea using ECG signals, where FAWT was used to decompose the signals and ML algorithms were applied to classify apnea events with high accuracy.

Recently, some authors have integrated the WT into DL-based approaches.

Recent studies have integrated WTs with DL approaches for EEG signal analysis. Asghar et al. (2022) proposed a method for emotion classification by decomposing EEG signals using multivariate empirical mode decomposition (MEMD) and then applying CCWT to extract features and generate spectrograms for further processing. Sobahi et al. (2022) used WT to extract EEG rhythms, followed by a One-Dimensional Local Binary Pattern (1D LBP) to create EEG images, which were then classified using CNN. Shen et al. (2023a) applied CWT to extract time-frequency features from EEG, using them to build functional connectivity matrices processed by a 3D CNN for classifying alcoholics versus controls. Fang et al. (2023) introduced a dual-stream neural network for sleep staging, using CWT for time-frequency representation as input to one stream and raw EEG to another, with adaptive boosting to address class imbalance. Malviya and

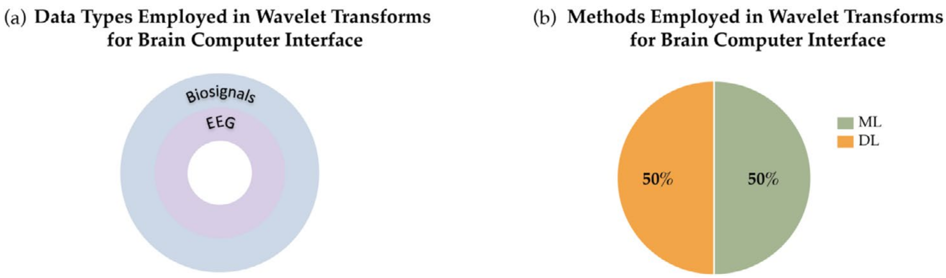

FIGURE 6 | Summary of the studies ($n = 6$) on wavelet and AI applied in the brain–computer interface. (a) Sunburst diagram (outer ring: biosignals/images), inner ring: data used; (b) pie-chart ML versus DL approaches.

Mal (2022) used DWT for noise removal and feature extraction from EEG signals, followed by CNN for automatic feature selection to detect stress.

Other studies use the PPG and ECG signals to assess conditions such as hypertension and mental stress. Martinez-Ríos et al. (2022) used WST to classify hypertension from PPG signals, extracting time-frequency features and applying them to an SVM classifier. Khan et al. (2023) decomposed PPG signals using DWT to classify hypertension and diabetes, with statistical features extracted from the sub-bands and classified using multiple ML classifiers. Barki and Chung (2023) applied CWT to transform PPG signals into scalograms, which were then classified as stressed or non-stressed using a CNN. Liang et al. (2018) used CWT to convert PPG signal segments into scalograms for input into a GoogLeNet pre-trained CNN for hypertension classification. Koh et al. (2022) applied EWT to ECG signals, extracting entropy-based features like approximate and permutation entropy for the classification of mental health disorders such as ADHD and conduct disorder.

Additionally, Rastgoo et al. (2021) developed an ECG-based driver stress classification system using particle swarm optimization for windowing hyperparameters. WT was part of an iterative pulse peak detection algorithm to analyze ECG signals. Jarchi et al. (2020) proposed a framework for recognizing patient groups with sleep disorders using both ECG and Electromyography (EMG) signals, employing WT to reliably extract heart rate and breathing-related features via an iterative pulse peak detection algorithm.

WTs have shown significant potential for assessing mental health, particularly in the analysis of EEG signals. These techniques are widely used for feature extraction and time-frequency domain representation, aiding in the classification of various mental health conditions such as stress, sleep disorders, and emotions, thus contributing to more accurate and reliable diagnostic systems.

3.3 | Brain–Computer Interface

Brain–Computer Interface (BCI) technology enables direct communication between the brain and external devices, offering a promising solution for individuals with severe motor disabilities. Figure 6 and Table A3 summarize the works reported in this section, the data types used, and the results obtained.

Both ML and DL approaches have been applied in the field of BCI, integrating WT into the processing pipelines, particularly for feature extraction and signal processing in EEG-based applications. For example, Kaur et al. (2019) utilized DWT for age and gender classification from EEG signals, extracting statistical features from different frequency bands. Aileni et al. (2020) applied DWT for early detection of epileptic seizures using artificial neural networks (ANNs). In motor imagery tasks, Collazos-Huertas et al. (2020) improved classification accuracy by using CWT to extract time-frequency planes for CNN-based classification. Other studies, such as Phadikar et al. (2023) and Chaudhary et al. (2020), explored feature extraction using WT and various classifiers to enhance the accuracy of motor imagery classification tasks. Additionally, Xu et al. (2019) leveraged WT to transform multichannel EEG signals into time-frequency images, which were then used as input for CNNs to classify motor imagery tasks.

These studies demonstrate the effectiveness of WT in various BCI applications, such as classification, seizure detection, and motor imagery. The integration of WT with AI improves signal analysis, classification accuracy, and system interpretability. However, challenges remain, including the need for more robust algorithms, better handling of variability, artifact removal, and enhanced real-time processing.

3.4 | Neurological Disorders

Neurological disorders encompass a wide range of conditions that affect the nervous system, including the brain, spinal cord, and peripheral nerves. Figure 7 and Table A4 summarize the works reported in this section, the data types used, and the results obtained.

In the study of neurological disorders, several studies have employed WT for both signal decomposition and feature extraction from EEG signals. DWT was frequently used to decompose EEG signals into different frequency sub-bands, from which various statistical and entropy-based features were extracted for classification using ML models, such as ANN, k-Nearest Neighbors (kNN), and SVM. Notable examples include Zeng et al. (2020), Durongbhan et al. (2019), and Chakrabarti et al. (2020), who applied DWT for epilepsy detection and classification, achieving high accuracy. Similarly, methods involving FAWT and TQWT were employed by You et al. (2020) and George et al. (2020) for focal and non-focal seizure detection and classification, utilizing entropy measures

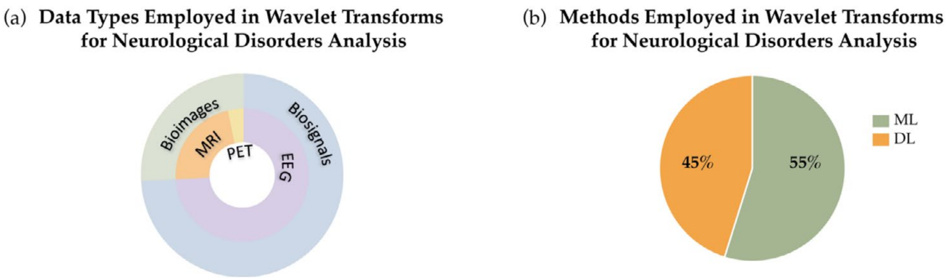

FIGURE 7 | Summary of the studies ($n=31$) on wavelet and AI applied in neurological disorders. (a) Sunburst diagram (outer ring: biosignals/images), inner ring: data used; (b) pie-chart ML versus DL approaches.

as key features. Other studies, such as Molla et al. (2020) and Yazid et al. (2021), focused on classifying seizures and non-seizures with DWT-derived features, achieving impressive classification results. Additionally, DWT-based approaches were applied by Alsharabi et al. (2022) and Aljalal et al. (2022) for diagnosing Alzheimer's and Parkinson's diseases through feature extraction from resting-state EEG signals.

Ieracitano et al. (2020) and Anuragi et al. (2022) both focus on feature extraction from EEG signals for neurological disorder classification. Ieracitano et al. (2020) used CWT for feature extraction to detect Alzheimer's disease, while Anuragi et al. (2022) employed the phase space representation of sub-band signals, derived from EEG decomposed using the Fourier-Bessel series expansion-based FBSE-EWT, for epileptic seizure classification. On the other hand, Qaisar and Hussain (2021) used the Autoregressive Burg technique for feature extraction in combination with the Rotation Forest classifier to detect epileptic seizures, focusing on signal analysis rather than decomposition.

More recently, DL-based methods have been applied to EEG data to study neurological disorders. Li et al. (2017) combined DWT with wavelet-based envelope analysis to extract significant features for epilepsy detection using neural networks. Similarly, Geng et al. (2016) proposed a method employing DWT for EEG decomposition, extracting features from the sub-bands for seizure classification with an improved WNN. Sayeed et al. (2019) also employed DWT to decompose EEG signals into sub-bands, extracting features from each for seizure detection. These approaches emphasize the combined use of WTs and ML for effective neurological disorder analysis. Cui et al. (2021) utilized CWT with a Morse mother wavelet to generate time-frequency graphs from EEG signals, which were combined into images and classified with a CNN to differentiate Alzheimer's, mild cognitive impairment, and healthy subjects. Kaur and Shashvat (2022) applied CWT to EEG signals to create scalograms that serve as inputs to a CNN for identifying epileptic activity. Zhang et al. (2022) used tunable Q-factor WT and packet transform to generate scalograms for Parkinson's disease diagnosis, feeding them into deep residual shrinkage networks for classification. These methods highlight the synergy between WTs and DL in extracting and leveraging time-frequency representations of EEG data.

Fukumori et al. (2022) and Ari et al. (2022) used WTs to extract EEG sub-bands, employing CNNs to detect epileptic spikes and autism, respectively, after feature extraction. Yan et al. (2022) and Shen et al. (2023b) employed TQWT to decompose EEG signals into sub-bands, using statistical features for real-time epilepsy seizure detection via CNN classifiers. Similarly, Chen et al. (2023) utilized DWT to extract sub-band features like approximate entropy for epileptic seizure detection.

WT methods are commonly used in MRI-based neurological disorder analysis, primarily for feature extraction. Siddiqui et al. (2015) and Gupta et al. (2020) utilized DWT to extract approximation and detailed features from MRI images for classification tasks, optimizing computational efficiency. Similar approaches were adopted by Kumar et al. (2021), Yılmaz Acar et al. (2022), and Arif et al. (2022), who applied DWT to extract spatial and spectral features, enabling effective brain tumor classification and disease activity prediction. Ma et al. (2020) employed WT for denoising and preprocessing MRI images, combined with the Laplacian of Gaussian (LoG) filtering, to prepare data for radiomics-based glioma grading models.

The sole study utilizing PET images, by Subramanyam Rallabandi and Seetharaman (2023), employed a DL approach for Alzheimer's disease classification. Their method integrates MRI and PET data, using 2D DWT as a preprocessing step for MRI images prior to fusion with PET images, enhancing the classification of Alzheimer's, mild cognitive impairments, and healthy controls.

Overall, WTs have proven highly effective in analyzing EEG, MRI, and PET data for neurological disorders. By enabling detailed signal decomposition and robust feature extraction, WT enhances the performance of ML and DL models in diagnosing conditions such as epilepsy, Alzheimer's, Parkinson's disease, and autism.

3.5 | Respiratory Disorders

Respiratory disorders refer to a broad range of medical conditions that affect the respiratory system, including the lungs, airways, and breathing muscles. Figure 8 and Table A5 summarize the works reported in this section, the data types used, and the results obtained.

Authors used both signals and images for the analysis of respiratory diseases. In ECG-based studies, Hassan and Haque (2017) utilized TQWT to decompose ECG signals and extract statistical features for sleep apnea detection, achieving superior performance. Similarly, Linh et al. (2023) employed CWT for feature extraction from single-lead ECG signals to detect apnea events

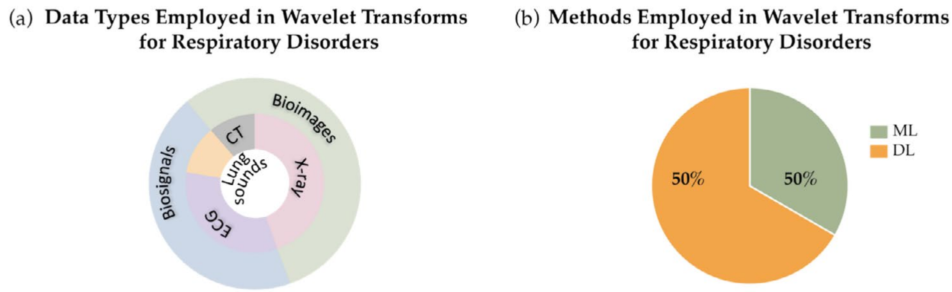

FIGURE 8 | Summary of the studies ($n = 10$) on wavelet and AI applied in respiratory disorders. (a) Sunburst diagram (outer ring: biosignals/images), inner ring: data used; (b) pie-chart ML versus DL approaches.

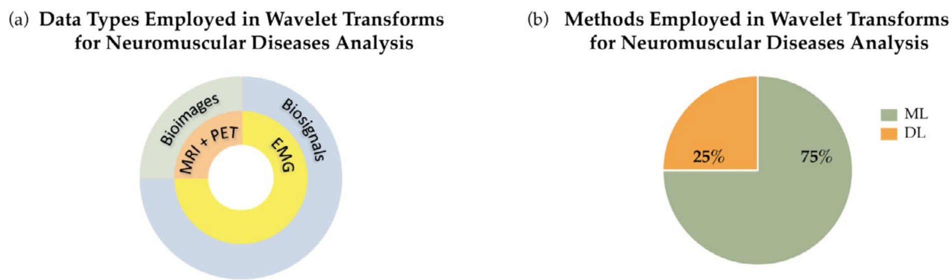

FIGURE 9 | Summary of the studies ($n = 4$) on wavelet and AI applied in neuromuscular disorders. (a) Sunburst diagram (outer ring: biosignals/images), inner ring: data used; (b) pie-chart ML versus DL approaches.

using ML classifiers. Attallah (2022) proposed ECG-BiCoNet for COVID-19 diagnosis, integrating DWT to reduce the dimensionality of deep features from CNN layers before classification.

For respiratory sound analysis, Shuvo et al. (2021) developed a lightweight CNN model using a hybrid approach combining Empirical Mode Decomposition (EMD) and CWT to generate scalograms from lung sound signals, which were then classified for disease identification.

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In the field of imaging, Patel and Kashyap (2022) employed 2D FAWT to denoise lung CT images and extract statistical features for COVID-19 detection, achieving high accuracy with SVM classification. For X-ray imaging, Muralidharan et al. (2022) used FB2DEWT to extract multiscale modes, which were input into a deep CNN for classifying X-rays into COVID-19, pneumonia, and normal classes. Huang et al. (2020) proposed a two-stage residual CNN (TS-RCNN) method for low-dose CT image denoising. In this approach, SWT is first applied to the CT images, followed by a CNN to denoise the wavelet coefficients, improving the texture quality of the images.

WT has proven effective in both signal and imaging-based analyses of respiratory diseases, enhancing feature extraction, noise reduction, and classification accuracy. Its integration with ML and DL models demonstrates significant potential for diagnosing conditions like COVID-19 and sleep apnea, leveraging the multiscale capabilities of WT to improve detection and classification outcomes.

3.6 | Neuromuscular Disorders

Neuromuscular disorders encompass a range of medical conditions that affect the nerves and muscles, leading to impaired muscle function and control. Figure 9 and Table A6 summarize the works reported in this section, the data types used, and the results obtained.

Subasi (2013) utilized DWT to extract statistical features from decomposed EMG signals for classifying normal, neurogenic, or myopathic signals with a Particle Swarm Optimization—Support Vector Machine (PSO-SVM) model. Later, Subasi (2020) combined multiscale PCA for denoising and DT-CWT for feature extraction, classifying EMG signals using a rotation forest ensemble. Subramani and Rani (2021) applied DWT for signal decomposition and integrated it with CNN to predict muscular paralysis.

For imaging, Preethi and Aishwarya (2021) employed DWT to decompose PET and MRI images, extracting statistical features from sub-bands for brain tumor detection and segmentation, highlighting wavelets' utility in medical imaging.

These studies demonstrate the versatility and effectiveness of WT in capturing critical features across both EMG signals and medical imaging for neuromuscular disorder diagnosis and analysis.

3.7 | Miscellaneous Application

This section encompasses all other studies not falling into the aforementioned categories. Table A7 summarizes the works presented in this section, including the data types used and the obtained results.

Zhang, Zhou, and Zeng (2017) used DWT for ECG-based biometric identification, applying it as a preprocessing step to decompose ECG segments into multiple wavelet components for enhanced feature extraction with CNN. In another study, Zhang, Zhao, et al. (2017) employed WT for ECG data compression, removing noise before feature extraction for signal distinction. Wulan et al. (2020) introduced WaveletGAN, a DL-based generative model that uses SWT to decompose ECG signals into coefficient time series for reconstruction. Sashidhar et al. (2021) applied WT to filtered ECG signals for generating scalograms, which were reduced using PCA and classified with linear discriminant analysis (LDA) to predict pulse presence during cardiac arrest. Guo, Wan, et al. (2022) used WT to preprocess PPG signals from wristbands for physical fitness evaluation, extracting physiological features before classifying them with a 1D CNN. Torbati et al. (2014) developed a noise-robust NN-based medical image segmentation method, using DWT to create feature spaces for improved pattern recognition. Singh et al. (2022) proposed a multimodal medical image fusion watermarking algorithm, using RDWT to embed watermarks in MRI and CT images.

4 | Discussion

4.1 | Summary of Main Findings

In this section, we summarize the main findings from our systematic review of the application of WT in healthcare using AI frameworks. The integration of WT and AI techniques has shown promising results and benefits in various healthcare domains. Figure 10 illustrates the publication trends over the years. We observed a consistent increase in the utilization of WT in healthcare applications. Notably, there was a significant surge in 2020 when WT started being employed also in image analysis and DL methodologies. This expansion into the field of images and DL showcases the versatility and adaptability of WT in addressing complex healthcare challenges.

Furthermore, Figure 10 provides insights into the distribution of works based on ML and DL approaches over the years. Before 2020, the application of WT was predominantly seen in ML. However, there has been a progressive shift toward utilizing WT as a feature extraction technique within DL methods. For instance, the work by Kaur and Shashvat (2022) exemplifies this approach, where signals are transformed into scalograms using WT, and DL algorithms are employed for classification tasks. This approach capitalizes on the ability of WT to analyze and extract patterns from data, coupled with the superior classification capabilities of DL compared to ML methods. Several authors followed the same approach in the field of neurodegenerative diseases (Zhang et al. 2022), cardiac abnormalities (Zhang et al. 2022), and respiratory disorders (Shuvo et al. 2021).

Figure 11a presents the distribution of works based on different tasks. The primary tasks involving WT in healthcare applications are detection and diagnosis, accounting for the majority of the studies ($n = 59$). Classification tasks rank second ($n = 32$), while tasks related to recognition and prediction are less prevalent. Additionally, the "other" category includes general tasks such as signal denoising, showcasing the diverse range of applications for WT in healthcare.

Figure 11b provides insights into the types of WT utilized in the reviewed studies. DWT emerges as the most widely used type, representing 43% of the studies. This preference can be attributed to its specific advantages, such as computational efficiency and multiresolution analysis (Zhang, Zhou, and Zeng 2017). In the application of WT and AI techniques in healthcare, DWT is frequently employed in the preprocessing stage. It is used to extract meaningful features from signals (Khan et al. 2023; Sengupta et al. 2018) and images (Arif et al. 2022), which are then used as input to ML or DL classifiers. Another commonly employed type is the CWT, which provides time-frequency localization (Kaur and Shashvat 2022).

CWT helps extract frequency-based features from biosignals or medical images, which are then utilized as input for ML or DL models. Another fairly utilized method is the TQWT, employed by 7% of the studies reported in this review. TQWT plays

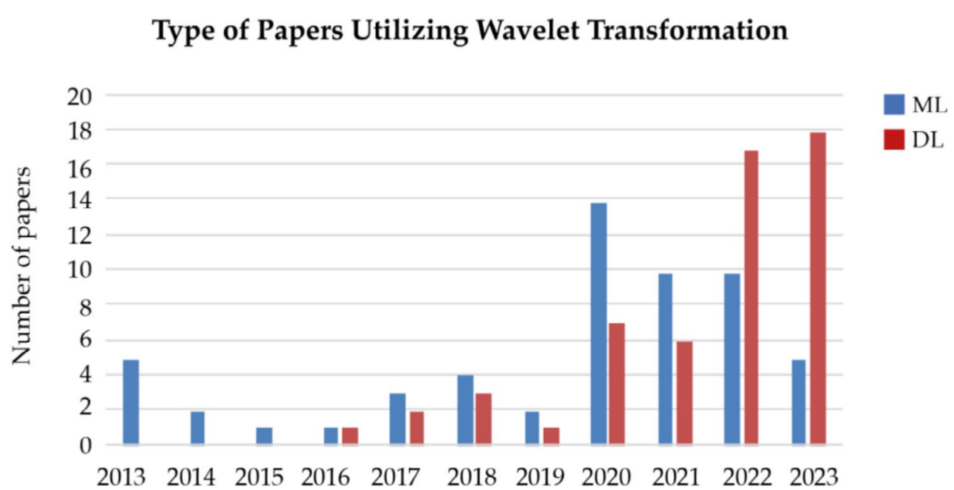

FIGURE 10 | Temporal distribution of reviewed papers categorized by the use of machine learning (ML) or deep learning (DL) approaches, divided by publication year.

an important role in the signal preprocessing/feature extraction step by decomposing signals into frequencies, allowing for more detailed analysis and improved classification when used with AI/ML techniques.

4.2 | Role of Wavelet and AI in Healthcare

Figure 12a shows the distribution of studies included in the review categorized by the different application areas. Cardiac abnormalities are the largest application area, with around 29% of studies falling under this category. This area looks at the detection and classification of various heart conditions using signals like ECG and PCG. Neurological disorders are the second largest category, with 27% of studies. These studies assessed conditions like epilepsy, Alzheimer's, and Parkinson's diseases, using EEG and MRI scans. Around 16% of studies focused on mental health, assessing conditions like stress and emotions using EEG signals. Respiratory disorders comprised around 8% of studies. The former analyzed conditions like COVID and sleep apnea. BCI and neuromuscular diseases accounted for around 5% and 4% of studies, respectively. BCI studies used EEG for tasks like motor imagery classification. Smaller categories included signal denoising (around 4% of studies) and miscellaneous applications (around 4%). This distribution highlights that significant research effort has gone into understanding cardiac and neurological conditions using AI+WT techniques. It also shows interest in emerging domains like respiratory disorders and BCI. Overall, Figure 12 provides a sense of the focus areas and relative emphasis given by researchers in applying wavelet-AI synergies across the different medical domains.

Figure 12b shows the distribution of studies based on the data type used. The majority (around 82%) of studies utilized biosignals such as ECG, EEG, PCG, and PPG for analysis. This emphasizes the prominent role of physiological signals in healthcare applications. In particular, ECG is widely employed for cardiology work (seen in 39 studies) due to its non-invasive nature. EEG is also popular for researching mental health (10 studies) and neurological disorders (23 studies) given its correlation to brain function. Around 18% of studies employed medical images, primarily CT, MRI, and X-rays, to assess various conditions. This demonstrates a growing interest in applying wavelet–AI methods in radiology. Only 7 out of the 112 analyzed studies utilized both signal and image data, highlighting limited efforts in multi-modality fusion to date. In summary, while biosignals currently dominate due to their relevance in many health domains as well as easier accessibility, the trend indicates an increase in utilizing medical imaging applications by leveraging recent advances in DL. Overall, computational capabilities and hardware accessibility will also influence this shift towards more image-based research over time.

In addition to the current applications and benefits of WT and AI in healthcare, the choice of the mother wavelet for a specific task is an important consideration that warrants further investigation in future work. The mother wavelet determines the properties and characteristics of the WT, such as frequency resolution, time localization, and smoothness. Different wavelets have varying abilities to capture certain features or patterns in medical data. While this review has discussed the use of WTs in healthcare applications, the selection of the appropriate mother wavelet for a particular task remains a topic of

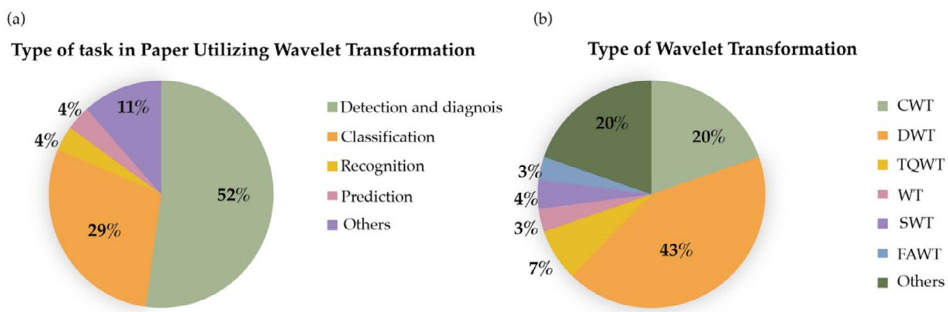

FIGURE 11 | (a) Task distribution leveraging WT analysis and (b) task distribution leveraging WT analysis.

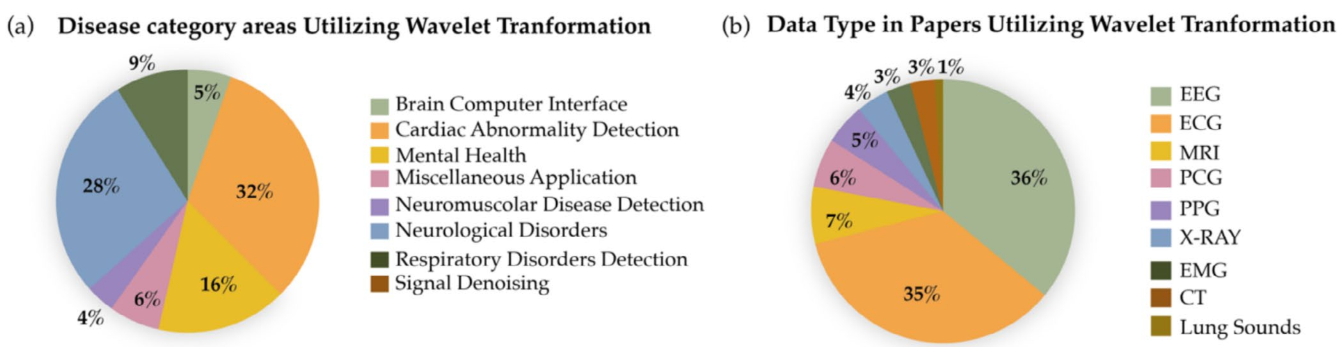

FIGURE 12 | (a) Distribution of works by application area and (b) the distribution of the data type used in WT + AI works in healthcare.

ongoing research. The choice of wavelet can have a significant impact on the accuracy and performance of the analysis, as different wavelets may be more suitable for specific types of signals or images.

4.3 | Comparative Analysis of Wavelet Transform Techniques

The comparative analysis of WT techniques reveals distinct performance patterns across healthcare applications. The DWT achieved its highest accuracy of 99.9% in epileptic seizure detection (Chen et al. 2023), while the CWT reached 99.18% accuracy in atrial fibrillation detection (Radhakrishnan et al. 2021). The TQWT demonstrated notable performance with 97.57% accuracy in epileptic seizure detection (Shen et al. 2023b), and the FAWT achieved 99.33% accuracy in motor-imagery tasks classification (Chaudhary et al. 2020). The EWT showed promising results with 96% accuracy in Covid-19 detection (Muralidharan et al. 2022), while the SWT demonstrated effective performance in texture denoising with a Peak Signal-to-Noise Ratio (PSNR) of 38.47 dB (Huang et al. 2020). Cross-WT applications, though less common, achieved 98% accuracy in phonocardiogram classification (Dhar et al. 2021). These results indicate that, while DWT and CWT generally achieve the highest accuracy levels, specialized WTs like TQWT and FAWT offer comparable performance with additional benefits in specific applications.

Beyond accuracy metrics, our review reveals several critical performance aspects of different WTs. DWT demonstrates superior computational efficiency, making it particularly suitable for real-time applications and resource-constrained environments, as evidenced in ECG-based systems (Mohamed Suhail and Abdul Razak 2022). CWT, while more computationally intensive, excels in capturing fine-grained temporal features, particularly beneficial in neurological applications where precise temporal localization is crucial (Cui et al. 2021). The choice between transforms often depends on the specific requirements of the medical application—DWT is predominantly used in biosignal analysis (82% of reviewed studies), while CWT is preferred in imaging applications where detailed frequency analysis is essential. Notably, newer transform variants like TQWT offer enhanced flexibility in controlling the Q-factor, proving particularly effective in analyzing oscillatory signals in mental health applications (Koh et al. 2022). The review also highlights a growing trend toward hybrid approaches, combining multiple WTs or integrating them with DL architectures, as seen in recent studies (Shuvo et al. 2023; Zhang et al. 2022), suggesting that future developments may lie in such combinatorial approaches rather than single transform applications.

4.4 | Benefits and Challenges of Wavelet in Healthcare

Wavelet transformation, when integrated with AI techniques, offers several benefits in healthcare applications. One of the key benefits of WT in healthcare is its ability to analyze biosignals and images at different frequencies and resolutions. This enables a more detailed analysis of underlying data, uncovering hidden patterns and extracting relevant features from medical data. By decomposing signals into various frequency components, WT provides a powerful mathematical framework that aids in the identification of anomalies and the understanding of complex physiological dynamics. The combination of WT and AI also facilitates real-time monitoring and diagnosis. WT can effectively capture subtle variations in physiological signals, even when these variations are very small yet clinically significant. AI algorithms can then analyze these transformed signals and provide actionable insights in real time, allowing for timely interventions and personalized treatment protocols. Wavelet-based methodologies further enhance the signal analysis process, especially in feature extraction. WT decomposes signals into multiple scales and resolutions, enabling the identification of both linear and nonlinear features (Zeng, Yuan, et al. 2023). This capability is particularly valuable in detecting anomalies or subtle signal changes that indicate disease progression or early-onset conditions.

Another advantage of WV lies in its ability to transform one-dimensional (1D) signals into 2D data representations, such as scalograms or wavelet spectrograms. These representations can be effectively processed by CNNs, which excel in image-based analysis. By utilizing the spatial and temporal features encoded in 2D WTs, CNNs can achieve remarkable accuracy in tasks such as arrhythmia detection, EEG-based seizure prediction, and other bioimaging applications. This approach closes the gap between traditional signal processing and advanced DL architectures, enabling automated and high-precision diagnostic systems.

Furthermore, WT in healthcare can contribute to the optimization of medical imaging. By utilizing wavelet techniques, medical images can be denoised, enhancing image quality and improving the accuracy of diagnostic interpretations. Additionally, wavelet-based image compression methods can reduce storage requirements while preserving essential diagnostic information.

Despite the several benefits, there are also challenges associated with the application of WT in healthcare (Figure 13). One such challenge is the selection of an appropriate wavelet basis function and scale for a specific application. This choice can significantly impact the accuracy and reliability of the analysis. Another challenge lies in the complexity of wavelet analysis algorithms and their computational requirements. Wavelet transformation involves mathematical computations, which can be computationally intensive, particularly when dealing with large datasets. Developing efficient and scalable algorithms for wavelet analysis in healthcare is essential to ensure real-time processing and practical implementation. Finally, the interpretation and clinical validation of wavelet-transformed data poses challenges. While wavelet analysis can uncover hidden patterns, the clinical significance and interpretation of these findings require domain expertise and validation.

4.5 | Future Research Directions

As the field of WT and AI continues to evolve, it is important to highlight emerging trends and potential future directions for

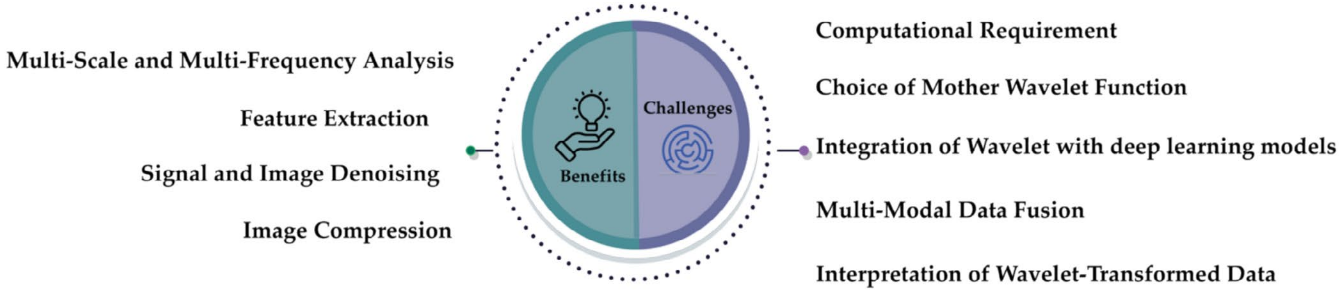

FIGURE 13 | Challenges and benefits of wavelet transformation in healthcare research discussed in this review.

healthcare applications. Several areas of improvement and future research opportunities exist to advance the field:

- *Optimization of Computational Efficiency*: wavelet-based studies often have significant computational costs, which can hinder their application, especially in real-time scenarios. Investigating methods to optimize the computational efficiency of WVs and their integration with AI models is, therefore, critical. Techniques such as quantization, model pruning, and edge computing can help reduce latency and make WT applications more feasible for real-time environments or wearable devices. For example, WTs could be used in continuous monitoring systems to analyze HRV in the frequency domain utilizing PPG data. Continuous, real-time monitoring of cardiovascular health would be made possible by incorporating such capabilities into wearable technology. These applications may become more useful and accessible by reducing the computing needs of WT processing, paving the way for broader healthcare usage.
- *Choice of mother WT*: Focus on exploring the selection criteria for choosing the optimal wavelet for different healthcare applications. This may involve considering factors such as the characteristics of the medical data, the desired level of frequency resolution, the presence of noise or artifacts, and the specific analysis goals.
- *Integration of WT with DL Techniques*: Investigate the use of WT within DL frameworks. WT's ability to capture localized signal features in the time-frequency domain could complement the powerful pattern recognition and hierarchical feature extraction capabilities of DL models, such as convolutional neural networks. This can leverage the strengths of both approaches to improve the performance of classification and detection tasks. More in detail, future studies could investigate methods to transform 1D signals into 2D representations, such as scalograms, for use as input to DL models. This approach has the potential to unlock new possibilities in fields like arrhythmia detection (Zhang et al. 2021), atrial fibrillation detection (Ma et al. 2021), and neurological disorder detection (Zhang et al. 2022). Additionally, researchers could investigate the use of WT as a preprocessing step to improve the efficiency of DL models by focusing on salient features and reducing noise in the data.
- *Multi-Modal Data Fusion*: Current applications often focus on single-modality data (e.g., EEG, ECG or images), limiting their applicability to complex conditions requiring multimodal analysis. Future research should explore methodologies to combine WT with other modalities, such as genetic data, text-based clinical records, or wearable sensor data. The fusion of multiple data sources can provide a holistic view of patient health, enabling more accurate and comprehensive decision-making (Salvi et al. 2024).
- *Explainability and Interpretability*: Focus on developing interpretable models and visualization techniques to enhance the transparency and trustworthiness of wavelet-based AI systems in healthcare. Visualization methods such as saliency maps could highlight which wavelet-derived features contribute most significantly to a model's decisions. This includes methods to explain the decisions or quantify the uncertainty of the predictions (Seoni et al. 2023), facilitating clinical validation and acceptance.

5 | Conclusion

The integration of wavelet transformation and AI in healthcare has demonstrated significant potential for advancing diagnostics and interventions. This review has provided insights into the application of WT within the AI framework, focusing on the most used wavelets, data types, and tasks in the medical field. The benefits of this integration include multi-scale and multi-frequency signal analysis, effective feature extraction, and improved signal/image denoising and compression. To further advance the field, future research should optimize computational efficiency and integrate more advanced AI techniques. Fusing data from multiple modalities and improving explainability will also be important. Addressing these challenges can help pave the way for more automated, real-time diagnostic tools with personalized treatment recommendations.

Author Contributions

Samiul Based Shuvo: conceptualization (equal), data curation (equal), formal analysis (supporting). **Syed Samiul Alam:** conceptualization (supporting), data curation (equal), formal analysis (supporting). **Syeda Umme Ayman:** data curation (supporting), investigation (supporting), writing – review and editing (supporting). **Arbil Chakma:** data curation (supporting), formal analysis (supporting), investigation (supporting). **Massimo Salvi:** supervision (supporting), visualization (supporting), writing – original draft (lead). **Silvia Seoni:** formal analysis (supporting), visualization (lead), writing – review and editing (supporting). **Prabal Datta Barua:** validation (supporting), writing – review and editing (supporting). **Filippo Molinari:** supervision (supporting), writing – review and editing (supporting). **U. Rajendra Acharya:** conceptualization (supporting), supervision (lead), writing – review and editing (lead).

Acknowledgments

Open access publishing facilitated by Politecnico di Torino, as part of the Wiley - CRUI-CARE agreement.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

All data used in this systematic review are available in the cited publications. The excel file with the search strategy, inclusion criteria, and data extraction are available from the corresponding author upon reasonable request.

Related WIREs Articles

Statistical analysis of fMRI using wavelets: Big Data, denoising, large-p-small-n matrices

Automatic diagnosis of sleep apnea from biomedical signals using artificial intelligence techniques: Methods, challenges, and future works

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Appendix A

TABLE A1 | Summary of studies conducted on cardiac abnormalities.

Author, year	Data type	Wavelet	Technique	Results/findings
Giri et al. (2013)	ECG	DWT	ML: SVM, kNN	96.8% classification accuracy, 100% sensitivity, and 93.7% specificity of normal and coronary artery disease states
Martis, Acharya, and Min (2013)	ECG	DWT	ML: SVM, NN, probabilistic network (PNN)	99.28% accuracy, 99.97% sensitivity, 99.83% specificity, and 99.21% PPV in arrhythmic beat classification
Martis, Acharya, Lim, et al. (2013)	ECG	DWT	ML: 3-layer feed-forward	94.52% accuracy, 98.61% sensitivity, and 98.41% specificity in arrhythmic beat classification
Poungponsri and Yu (2013)	ECG	DWT	ML: ANN	Improvement in terms of SNR of 15.7 dB in noise removal
Martis et al. (2014)	ECG	DWT	ML: DT, ANN, kNN	99.45% accuracy, 99.61% sensitivity, and 100% specificity, in arrhythmic beat classification
Elhaj et al. (2016)	ECG	DWT	ML: SVM, NN	98.91% accuracy in arrhythmic beat classification
Gutiérrez-Gnecchi et al. (2017)	ECG	DWT	ML: PNN	92.75% accuracy in arrhythmic beat classification
Adam et al. (2018)	ECG	DWT	ML: kNN	99.27% accuracy, 99.74% sensitivity, 98.08% specificity in arrhythmias detection
Sengupta et al. (2018)	ECG	CWT	ML: RF	91% AUC, 80% sensitivity, and 84% specificity for prediction of abnormal myocardial mechanical relaxation
Venkatesan et al. (2018)	ECG	DWT	ML: SVM	96% accuracy in arrhythmic beat classification
Xia et al. (2018)	ECG	STFT, SWT	DL: CNN	99.29% accuracy, 98.34% sensitivity, and 98.24% specificity in atrial fibrillation detection
Tuncer et al. (2019)	ECG	DWT	ML: kNN	95.0% accuracy in arrhythmia detection
Bashar, Han, et al. (2021)	ECG	DWT	ML: SVM	98.99% sensitivity, 95.18% specificity and 97.45% accuracy in atrial fibrillation prediction
Jothiramalingam et al. (2021)	ECG	CWT	ML: SVM, kNN	97.8% accuracy in left ventricular hypertrophy
Ma et al. (2021)	ECG	Modified frequency slice wavelet transform	DL: CNN	93.03%, 98.61%, 97.04% accuracies in atrial fibrillation detection

(Continues)

TABLE A1 | (Continued)

Author, year	Data type	Wavelet	Technique	Results/findings
Panda et al. (2020)	ECG	EWT	DL: CNN	Accuracy of 99.036%, 99.800%, and 81.250% for the classification between ventricular fibrillation and other cardiac pathologies
Zeng et al. (2021)	PCG	TQWT	ML: standard radial basis function (RBF) neural networks	Sensitivity, specificity, overall score and accuracy values of 97.73%, 98.05%, 97.89%, and 97.89%, respectively in abnormal heart sound signals detection
Bashar, Han, et al. (2021)	ECG	TQWT	ML: SVM, RF	90% accuracy, 80% sensitivity, 100% specificity, 100% PPV, and 83.33% NPV in atrial fibrillation prediction
Dhar et al. (2021)	PCG	Cross-wavelet transform	DL: 2D CNN	Accuracy of 98% and 97.89% with the raw and the de-noised PCG dataset in phonocardiogram signals classification
Radhakrishnan et al. (2021)	ECG	Chirplet transform	DL: LSTM	99.18% accuracy, 99.17% sensitivity, and 99.18% specificity in atrial fibrillation detection
Sawant et al. (2021)	PCG	TQWT	ML: Light Gradient Boosting	Sensitivity of 89.30%, specificity of 91.20%, and an overall score of 90.25% in abnormal heart sound signal detection
Zhang et al. (2021)	ECG	CWT	DL: Inception-ResNet-v2	84.4% F1-score in cardiac arrhythmia classification
Houssein et al. (2022)	ECG	DWT	DL: Marine Predators algorithm + CNN	Accuracy levels, 99.33% (MIT-BIH), 99.75% (EDB), and 99.43% (INCART) in arrhythmia classification
Li et al. (2022)	ECG	DWT	DL: CNN-LSTM neural networks	Sensitivity, PPV, and specificity, in arrhythmia classification, equal to 94.54%, 93.33%, 80.80% for normal segments, 35.22%, 65.88%, 98.83% for the supraventricular ectopic segment, 88.35%, 79.86%, 94.92% for the ventricular ectopic segment
Peng et al. (2022)	ECG	DWT	DL: CNN + BiLSTM	99.28% accuracy, and 95.70% Macro-F1 score in arrhythmic beat classification
Mohamed Suhail and Abdul Razak (2022)	ECG	DWT	ML: Nonlinear Vector Decomposed Neural Network	90.67% accuracy, 92.0% sensitivity, and 89.33% specificity in cardiac disease detection
Chatterjee et al. (2022)	ECG	CWT	DL: Autoencoder NN	Improvement in terms of SNR (27.8 dB) is obtained over the state-of-the-art ECG de-noising methods

(Continues)

TABLE A1 | (Continued)

Author, year	Data type	Wavelet	Technique	Results/findings
Ahmed et al. (2023)	PPG	FWT	ML: Feed forward neural network	Reduction of the MSE of the PPG signal: 56.40% for Gaussian noise, 64.01% for Poisson noise, 46.02% for uniform noise, and 72.36% for salt-and-pepper noise.
Zeng, Yuan, et al. (2023)	ECG	DWT	ML: RBF neural networks	98.81% accuracy in myocardial dysfunction detection
Zeng, Su, Yuan, and Chen (2023)	PCG	Rational dilation wavelet transform	DL: 1D CNN	98.10% accuracy in heart valve disorder detection
Zeng, Su, Chen, and Yuan (2023)	ECG	TQWT	DL: CNN-LSTM neural networks	96.13% accuracy in arrhythmia detection
Bhardwaj et al. (2023)	PCG	CWT	DL: 2D CNN	93.07% accuracy in valvular heart disease classification
Karri and Annavarapu (2023)	ECG	DWT	DL: LSTM	99.64% accuracy, 99.15% PPV, 99.87% sensitivity, and 98.18% F1-score in arrhythmia classification
Kim et al. (2023)	ECG	WT	DL: CNN + SIncNEt	Nearly 90% overall accuracy and 91.4%, 49.3%, and 91.4% sensitivity for non-ectopic, supraventricular ectopic, and ventricular ectopic beat classifications, respectively
Rajeshwari et al. (2023)	PCG	CWT	DL: 1D + 2D CNN	98.6% accuracies in mitral valve prolapse detection
Shuvo et al. (2023)	PCG	CWT	DL: Convolutional Recurrent Neural Network	97.4% accuracy in valvular cardiac disease detection

TABLE A2 | Summary of studies conducted on mental health.

Author, year	Data type	Wavelet	Technique	Results/findings
Liang et al. (2018)	PPG	CWT	DL: Pretrained GoogleNET	F-scores of 80.52%, 92.55%, and 82.95% in NT (normotension) vs. PHT (prehypertension), NT vs. HT (hypertension), and (NT + PHT) vs. HT
Kumar Upadhyay and Nagpal (2020)	EEG	CWT	ML: Radial Basis NN and SVM	Accuracy of 96.4% under chronic stress, 94.1% for acute stress and the overall accuracy of 87% in the classification of sleep–wake states
Jarchi et al. (2020)	ECG, EMG	SSWT	DL: DNN	Accuracy of 72% and F1 score of 57% in recognition of patient groups with sleep-related disorders
Rastgoo et al. (2021)	ECG	Normalized CWT + Morse Wavelet	DL: 2D CNN (Transfer Learning)	92.12% and 77.78% accuracy on two datasets in stress level detection
Tuncer et al. (2021)	EEG	TQWT	ML: kNN, SVM	99.82% accuracy in emotion recognition
Asghar et al. (2022)	EEG	EMD, CCWT	DL: DNN	96.3% accuracy in emotion classification
Tor et al. (2021)	EEG	EMD, DWT	ML: kNN	Accuracy of 97.88% in detection of conduct disorder and attention deficit hyperactivity disorder
Sharma et al. (2022)	EEG	SWT	ML: SVM	Accuracy of 97.26% in mental stress detection
Pant et al. (2022)	EEG	FAWT-flexible analytic wavelet transform	ML: kNN	94.52% accuracy in sleep apnea detection
Malviya and Mal (2022)	EEG	DWT	DL: CNN + 1BiLSTM	Accuracy of 98.10% in stress detection
Sobahi et al. (2022)	EEG	CWT	DL: CNN	97.7% accuracy in schizophrenia detection
Martinez-Ríos et al. (2022)	PPG	WST	ML: SVM	Accuracy of 71.42% and an F1-score of 76% classifying normotension and prehypertension
Koh et al. (2022)	ECG	EWT	ML: Bagged Tree	87.19%, 87.71% and 86.29% for accuracy, sensitivity and specificity in the classification of attention deficit hyperactivity disorder
Fang et al. (2023)	EEG	CWT	DL: Modified ResNet50	85.8%, and 81.0% accuracy on two datasets in sleep stage classification
Shen et al. (2023a)	EEG	CWT	DL: CNN	96.25% accuracy and 98.06% F1-score in the detection of alcoholic EEG signals
Gosala et al. (2023)	EEG	CWT, DWT, WST	ML: SVM, LR	97.98%, 98.2%, 97.72% of accuracy, sensitivity, and specificity, respectively in schizophrenia classification
Barki and Chung (2023)	PPG	CWT	DL: CNN	Accuracy of 92.04% and F1-score of 90.8% in mental stress detection
Khan et al. (2023)	PPG	EMD	ML: kNN	F1 score of 92%, 98.5%, 98.3% in normotension vs. prehypertension and hypertension

TABLE A3 | Summary of studies conducted on brain-computer interface.

Author, year	Data type	Wavelet	Technique	Results/findings
Kaur et al. (2019)	EEG	DWT	ML: RF	Accuracy of 88.33% and 96.66% in age and gender prediction
Xu et al. (2019)	EEG	WT	DL: 2D CNN	Accuracy of 90% in motor imagery EEG classification
Collazos-Huertas et al. (2020)	EEG	CWT	DL: CNN	CWT improves the accuracy and enhances the interpretability of CNN architecture
Aileni et al. (2020)	EEG	DWT	ML: ANN	91.1% accuracy in brain activity classification
Chaudhary et al. (2020)	EEG	FAWT	ML: kNN	Accuracy 99.33%, sensitivity 99%, specificity 99.6%, and F1-Score 99.25% in motor-imagery tasks classification
Phadikar et al. (2023)	EEG	WT	DL: Autoencoder NN	Accuracy of 95.33% and 97% on two datasets in multiclass motor classification

TABLE A4 | Summary of studies conducted on neurological disorders.

Author, year	Data type	Wavelet	Technique	Results/findings
Siddiqui et al. (2015)	MRI	DWT	ML: LS-SVM	100% accuracy rate in Brain MRI Scans Classification
Geng et al. (2016)	EEG	CWT	DL: CNN	Sensitivity of 96.72%, specificity of 98.91% in epileptic seizure detection
Li et al. (2017)	EEG	DWT	DL: neural network ensemble	98.78% accuracy in epilepsy EEG signals classification
Sayeed et al. (2019)	EEG	DWT	DL: DNN	Accuracy of 100% for a classification of normal vs. ictal EEG and 98.6% for normal and interictal vs. ictal EEG
Zeng et al. (2020)	EEG	DWT	ML: RBF neural networks	98.15% accuracy detection of seizure EEG signals
Durongbhan et al. (2019)	EEG	FFT, CWT	ML: kNN	99% dementia classification accuracy
Ma et al. (2020)	MRI	WT	ML: XGBoost	Accuracy, sensitivity, specificity, and AUC equal to 83%, 86%, 81%, and 86%, respectively, in gliomas grading
Gupta et al. (2020)	MRI	DWT	ML: SVM, kNN, RF	Accuracy of 88%, sensitivity of 84%, and specificity of 92% in tumor classification
Chakrabarti et al. (2020)	EEG	DWT	ML: ANN	Accuracy, sensitivity and specificity of 95.3%, 97.2% and 93.5% in pediatric epileptic seizure detection
You et al. (2020)	EEG	FAWT	ML: SVM, kNN	Accuracy of 94.80% in focal and non-focal EEG detection
George et al. (2020)	EEG	TQWT	ML: Particle Swarm Optimization (PSO) and ANN	Accuracy of 95.1% (normal-focal), 97.4% (normal-generalized), 96.2% (normal-focal + generalized) and 88.8% (normal-focal-generalized) in epileptic EEG signals classification
Ieracitano et al. (2020)	EEG	CWT	ML: MLP, AE, SVM, LR	Accuracy of 96.95% in AD (Alzheimer's disease) vs. HC (Healthy Control), 90.24% in AD vs. MCI (Mild Cognitive Impairment), 96.24% in MCI vs. HC, 89.22% in AD vs. MCI vs. HC
Molla et al. (2020)	EEG	DWT	ML: FFNN	Accuracy of 99.55% in epileptic seizure detection
Kumar et al. (2021)	MRI	DWT	ML: RF, DT	Accuracy, sensitivity, specificity, F1-score, Matthew's correlation coefficient, AUC of 98.60%, 99.05%, 97.33%, 99.05%, 96.42%, 98.19% in brain tumor classification
Yazid et al. (2021)	EEG	DWT	ML: SVM, kNN	99.1% accuracy in epilepsy detection
Cui et al. (2021)	EEG	CWT	DL: Modified AlexNet	Accuracy of 98.9% in three-class classification of Alzheimer's disease (AD vs. mild cognitive impairment vs. healthy aging)
Qaisar and Hussain (2021)	EEG	DWT	ML: KNN, ANN, SVM	100% accuracy in epileptic seizure detection
Alsharabi et al. (2022)	EEG	DWT	ML: LDA, SVM, kNN, RF, DT	Accuracy of 99.98% in the classification of Alzheimer's disorders
Kaur and Shashvat (2022)	EEG	CWT	DL: 2D CNN	Accuracy of 91.7% in identification of epileptic activity
Zhang et al. (2022)	EEG	TQWT + WPT	DL: Deep Residual Shrinkage Network	Accuracy of 97.81% (3-class) and 92.59% (4-class) using WPT, 95.20% (3-class) and 90.46% (4-class) using TQWT, in the classification of Parkinson's disease

(Continues)

TABLE A4 | (Continued)

Author, year	Data type	Wavelet	Technique	Results/findings
Yılmaz Acar et al. (2022)	MRI	DWT	ML: SVM	F1-score, precision, and recall of 95.0% in future activity prediction of multiple sclerosis
Anuragi et al. (2022)	EEG	Empirical WT based on the Fourier Bessel series expansion	ML: SVM, RF	Accuracy of 100% in epileptic seizure classification
Kumar (2023)	MRI	DWT	DL: CNN	Accuracy of Otsu's, water- shed, level set, K-means, DWT, and CNN methods is 71.42%, 78.26%, 80.45%, 84.34%, 86.95%, and 91.39% in brain tumor detection
Fukumori et al. (2022)	EEG	DWT	DL: CNN	AUC of 96.7% in epileptic spike detection
Arif et al. (2022)	MRI	DWT	DL: GA U-Net	Accuracy of 97%, sensitivity of 98%, and specificity of 98% in brain tumor classification
Aljalal et al. (2022)	EEG	DWT	ML: kNN	Accuracy, sensitivity, and specificity of 99.89%, 99.87%, and 99.91% in Parkinson's disease detection
Ari et al. (2022)	EEG	DWT	DL: CNN	Accuracy of 98.88%, sensitivity of 100% and specificity of 96.4%, and the F1-score of 99.19% in the detection of autism spectrum disorders
Yan et al. (2022)	EEG	CWT	DL: CNN	Accuracy of 94.7% in epileptic seizure detection
Shen et al. (2023b)	EEG	TQWT	DL: 2D CNN	97.57% accuracy, 98.90% sensitivity in epileptic seizure detection
Subramanyam Rallabandi and Seetharaman (2023)	PET	DWT	DL: Inception and Residual Net	Accuracy of 95.5%, 94.1%, and 95.9% in classifying HC vs. MCI, MCI vs. AD, and AD vs. HC
Chen et al. (2023)	EEG	DWT	DL: CNN	Accuracy of 99.9%, a sensitivity of 100%, a precision of 99.81%, and a specificity of 99.8% in epileptic seizure detection

TABLE A5 | Summary of studies conducted on respiratory disorders.

Author, year	Data type	Wavelet	Technique	Results/findings
Hassan and Haque (2017)	ECG	TQWT	ML: Random under sampling boosting	88.88% accuracy, 87.58% sensitivity, and 91.49% specificity for automated identification of obstructive sleep apnea
Shuvo et al. (2021)	Lung sound	CWT	DL: 2D CNN	Accuracy of 98.92% for three-class chronic classification and 98.70% for six-class pathological classification
(Mostafiz et al. (2022)	X-Ray	DWT	DL: CNN	Accuracy of more than 98.5% in Covid-19 detection
Huang et al. (2020)	CT images	SWT	DL: RCNN	PNSR of 38.47 dB and SSIM equal to 0.881
Attallah (2022)	ECG	DWT	DL: CNN	Promising COVID-19 performance with an accuracy of 98.8% and 91.73% for binary and multiclass classification categories
Muralidharan et al. (2022)	X-Ray	EWT	DL: CNN	Accuracy of 96% and 100% for the multiclass and binary Covid-19 classification
Patel and Kashyap (2022)	CT images	FAWT	ML: SVM	Accuracy of 93.47%, specificity 93.34%, sensitivity 93.6% and F1-score 0.93 in Covid-19 detection
Hadi et al. (2023)	X-Ray	DWT	DL: CNN + LSTM	Accuracy of 99.57% in Covid-19 detection
Soundrapandiyan et al. (2023)	X-Ray	DWT	DL: WavStaCovNet-19	Accuracy of 94.24% and 96.10% on 4 classes and 3 classes in Covid-19 detection
Linh et al. (2023)	ECG	CWT	ML: SVM	Accuracy of 98.2%, and a F1-score of 93% in the detection of preceding sleep apnea

TABLE A6 | Summary of studies conducted on neuromuscular diseases.

Author, year	Data type	Wavelet	Technique	Results/findings
Subasi (2013)	EMG	DWT	ML: PSO + SVM	Accuracy of 97.41% in the diagnosis
Subasi (2020)	EMG	DT-CWT	ML: rotation forest ensemble	Accuracy of 99.7% in neuromuscular disorders
Preethi and Aishwarya (2021)	PET, MRI	DWT	ML: genetic algorithm and neural networks	Accuracy of 93% in brain tumor detection
Preethi and Aishwarya (2021)	EMG	DWT	DL: CNN	88% of precision in prediction of muscular paralysis disease

TABLE A7 | Summary of studies on studies conducted on miscellaneous applications.

Author, year	Data type	Wavelet	Technique	Results/findings
Torbati et al. (2014)	Xray, CT, MRI	DWT	ML: Supervised NN	93% sensitivity in segmentation of white matter from brain images
Zhang, Zhou, and Zeng (2017)	ECG	DWT	DL: 1D CNN	Identification rate of 93.5% in ECG-based biometric human identification
Zhang, Zhao, et al. (2017)	ECG	DWT	ML: ANN	Compression model achieves a high data compression ratio at 1:19 without losing important ECG information
Wulan et al. (2020)	ECG	SFTF, SWT	DL: GAN	Effective method for generating ECG signals with deep neural networks
Sashidhar et al. (2021)	ECG	DWT	ML: PCA + linear discriminant model	AUC of 0.84 in predicting pulse presence during chest compression
Singh et al. (2022)	MRI + CT images	Redundant DWT	DL: Denoising Convolutional Neural Network	Encryption of medical images for telehealth applications
Guo, Wan, et al. (2022)	PPG	CWT	DL: 1D CNN + LSTM	Accuracy of 98.27% for boys' physical fitness prediction, and 99.26% for girls' physical fitness prediction