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State-of-the-Art in Medical Image Watermarking: Current Innovations and Future Prospects

Bhupendra Kumar Bhardwaj[1], Prof. (Dr.) Satya Singh[2], Jullius Kumar[3]

[1,2]Department of Computer Science & Applications, M.G. Kashi Vidyapith, Varanasi, India
[3]Department of Computer Science & Information System, Sri Ramswaroop Memorial University

ABSTRACT
Watermarking techniques present a valuable approach to securing these sensitive medical images, balancing imperceptibility, robustness, and capacity. It explores recent advancements in watermarking techniques applied to medical images, focusing on their practical applications and efficacy. The integration of advanced technologies such as machine learning, deep learning, biometrics, and blockchain has significantly bolstered the capabilities of protecting medical image data. The review examines various watermarking methods, including spatial and transform domain techniques, compression, encryption, and their combinations. Additionally, it underscores the diverse applications of medical imaging across different domains, recent innovations, and the role of image processing and analysis methods like segmentation, feature extraction, and computer-aided diagnosis. The transformative impact of machine learning and deep learning models in medical imaging is discussed, alongside the critical importance of security and privacy measures, encompassing encryption and blockchain solutions. This review aims to provide insights into the effectiveness of these techniques and their future potential in advancing medical imaging practices.

KEYWORDS: Data hiding, Medical image, Watermarking techniques, Attacks, Metrics.

1. INTRODUCTION
With the increasing digitization of medical records, protecting the confidentiality, integrity, and authenticity of medical images has become crucial [1]. Watermarking techniques offer a viable solution to secure these sensitive images. Watermarking techniques applied to medical images, focusing on their robustness, imperceptibility, and practical applications [2]. The advent of digital technologies in healthcare has revolutionized the way medical data is generated, stored, and transmitted. Among various forms of medical data, medical images play a crucial role in diagnostics, treatment planning, and patient monitoring [3]. However, the increasing digitization and sharing of medical images have raised significant concerns regarding their security, privacy, and integrity [4]. Ensuring the protection of these sensitive images is essential to maintain patient confidentiality, prevent unauthorized access, and safeguard against tampering [5]. To address these challenges, various techniques have been developed for securing medical images, each with its own strengths and applications. These techniques can be broadly categorized into spatial domain methods, transform domain methods, compression, encryption, and combinations thereof. Additionally, the integration of advanced technologies such as machine

learning, deep learning, biometrics, and blockchain has further enhanced the capabilities of medical image protection [6]. This review aims to provide a comprehensive overview of the latest advancements in these areas, highlighting their effectiveness and potential for future applications [7]. Medical imaging plays a crucial role in modern healthcare, providing non-invasive methods for diagnosis, treatment planning, and patient monitoring. This review explores the diverse applications of medical imaging across different domains, highlighting advancements, challenges, and future directions. Imaging Modalities serve distinct purposes in medical imaging, each offering unique advantages and challenges [8]. X-ray Imaging having applications in skeletal imaging, pulmonary studies, and interventional radiology. CT gives High-resolution imaging for detailed anatomical visualization and 3D reconstruction [9]. MRI has superior soft tissue contrast for neurological, cardiac, and musculoskeletal imaging [10]. Ultrasound Imaging is real-time imaging for obstetrics, vascular studies, and guided interventions [11]. Nuclear Medicine has functional imaging techniques like PET and SPECT for oncology, cardiology, and neurology [12]. The role of Clinical Applications supports a wide array of clinical applications, influencing diagnosis, treatment decisions, and patient outcomes [13]. Recent Advances such as Oncology Imaging for tumor detection, staging, and treatment response assessment. Cardiology Imaging techniques for assessing heart function, coronary artery disease, and congenital heart abnormalities. Neurology has Neuroimaging for brain structure analysis, stroke diagnosis, and neurodegenerative disorders [14]. Orthopedics Imaging modalities for bone fractures, joint disorders, and sports injuries [15]. Pulmonology Imaging in respiratory diseases such as pneumonia, tuberculosis, and COPD [16]. The role of Image Processing and Analysis which Advances image processing techniques enhance diagnostic accuracy, facilitate quantitative analysis, and support image-guided interventions. Image Segmentation techniques for delineating anatomical structures and tumors in medical images [17]. Feature Extraction provides Quantitative analysis of image features for disease characterization and classification [18]. CAD proposed automated systems for assisting radiologists in detecting abnormalities and making diagnostic decisions [19]. Image Fusion: Integration of multi-modal images for comprehensive patient evaluation. VR and AR: Applications in surgical planning, education, and training using 3D reconstructed images [20]. The role of ML and DL techniques are revolutionizing medical imaging by enabling automated analysis, predictive modelling, and personalized medicine. Deep learning models for image classification, segmentation, and anomaly detection. Transfer Learning Adaptation of pre-trained models to medical imaging tasks with limited labeled data. Radiomics and Radiogenomics Quantitative analysis of imaging data to extract biomarkers for predicting treatment response and patient outcomes [21]. GANs Image synthesis and data augmentation techniques for improving training data diversity and model robustness. Security and Privacy ensures the confidentiality, integrity, and availability of medical image data to protect patient privacy and prevent unauthorized access [22]. Blockchain Technology Secure and transparent storage, sharing, and auditing of medical image data [23]. Encryption and Watermarking techniques for embedding and protecting digital watermarks and encrypting sensitive image data [24]. Some general terms describe in figure 1 and definitions used in the area of watermarking.

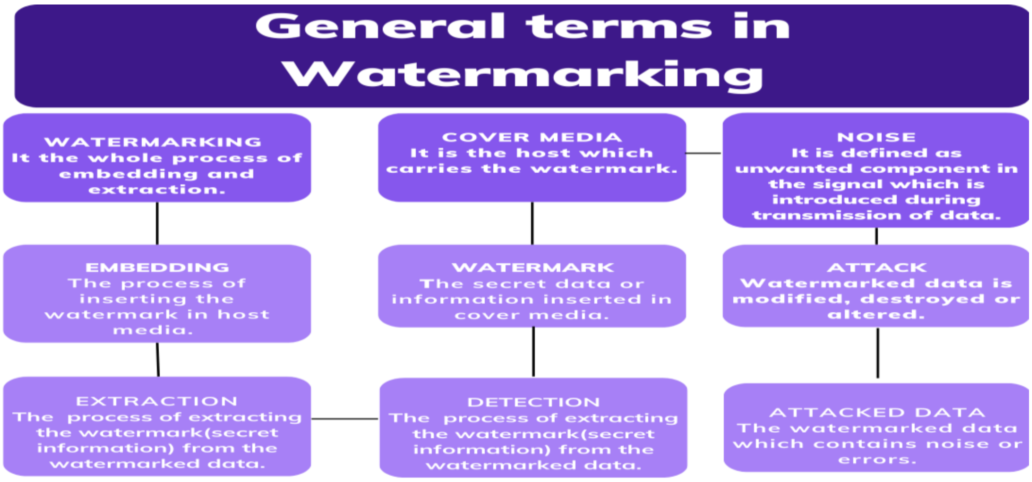

Figure-1: General terms in Watermarking.

Medical image watermarking is a technique used to embed information into medical images for purposes such as authentication, copyright protection, and secure communication [25]. The trade-off of a watermarking system is often evaluated based on three key parameters: imperceptibility, robustness, and capacity as describe in Table 1 and illustrated in figure 2 [26]. More over figure 3 describes the evolution of watermarking system in different periods. Figure 4 define the various attack in watermarking system and Table 2 discusses the various hybrid attacks in watermarking system [27].

Table 1: The trade-off between three key parameters Imperceptibility, Robustness and capacity.

Parameters	**Descriptions**	**Trade-Off with Imperceptibility**	**Trade-Off with Robustness**	**Trade-Off with Capacity**	**Balancing Strategies**
Imperceptibility	Degree to which the watermark is invisible to the human eye.	Embedding in less visible areas (high-frequency regions) may reduce robustness, essential for preserving diagnostic quality.	Embedding in robust areas (low-frequency regions) may reduce imperceptibility, potentially impacting the diagnostic utility of images.	Higher capacity can make the watermark more noticeable and degrade image quality, affecting clinical interpretation.	Use adaptive techniques to embed in non-diagnostic, visually complex regions. Optimize embedding strength to balance visibility and robustness.
Robustness	The ability of the watermark (secrete information)	Highly imperceptible watermarks are often less robust due to	Higher capacity may require more robust embedding, reducing	Embedding more data can reduce robustness if not handled	Use hybrid techniques combining spatial and frequency

	to with stand various attacks and processing operations.	embedding in less secure areas, making them vulnerable to standard medical image processing like compression and filtering.	imperceptibility and potentially affecting image clarity.	properly, making the watermark susceptible to tampering or accidental removal during routine processing.	domains to ensure watermarks survive medical image compression and processing. Optimize redundancy to enhance robustness without sacrificing imperceptibility.
Capacity	Amount of information that can be embedded without degrading image quality	Higher capacity can reduce imperceptibility due to more visible changes, which is critical in medical images where clarity is paramount.	More data requires more robust embedding, potentially reducing imperceptibility and affecting the diagnostic features of the image.	High capacity can affect both imperceptibility and robustness, crucial in medical images where maintaining image quality and watermark integrity is essential.	Employ hybrid and optimization methods to balance capacity with robustness and imperceptibility.

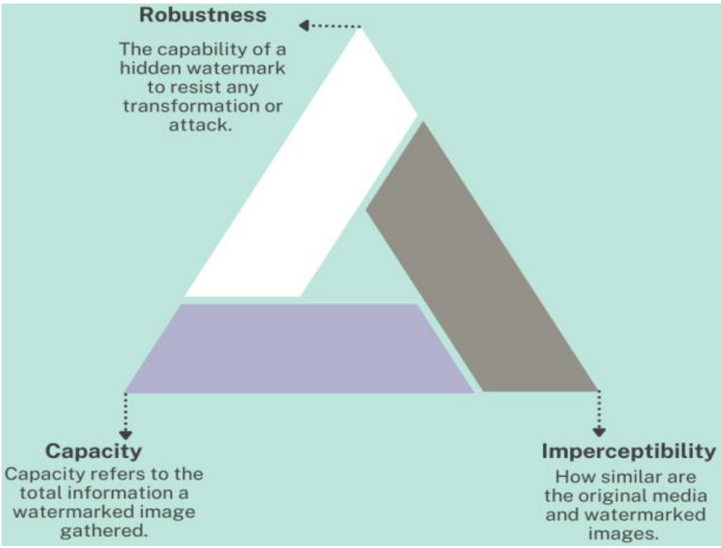

Figure 2: Trade-Offs in Watermarking Systems.

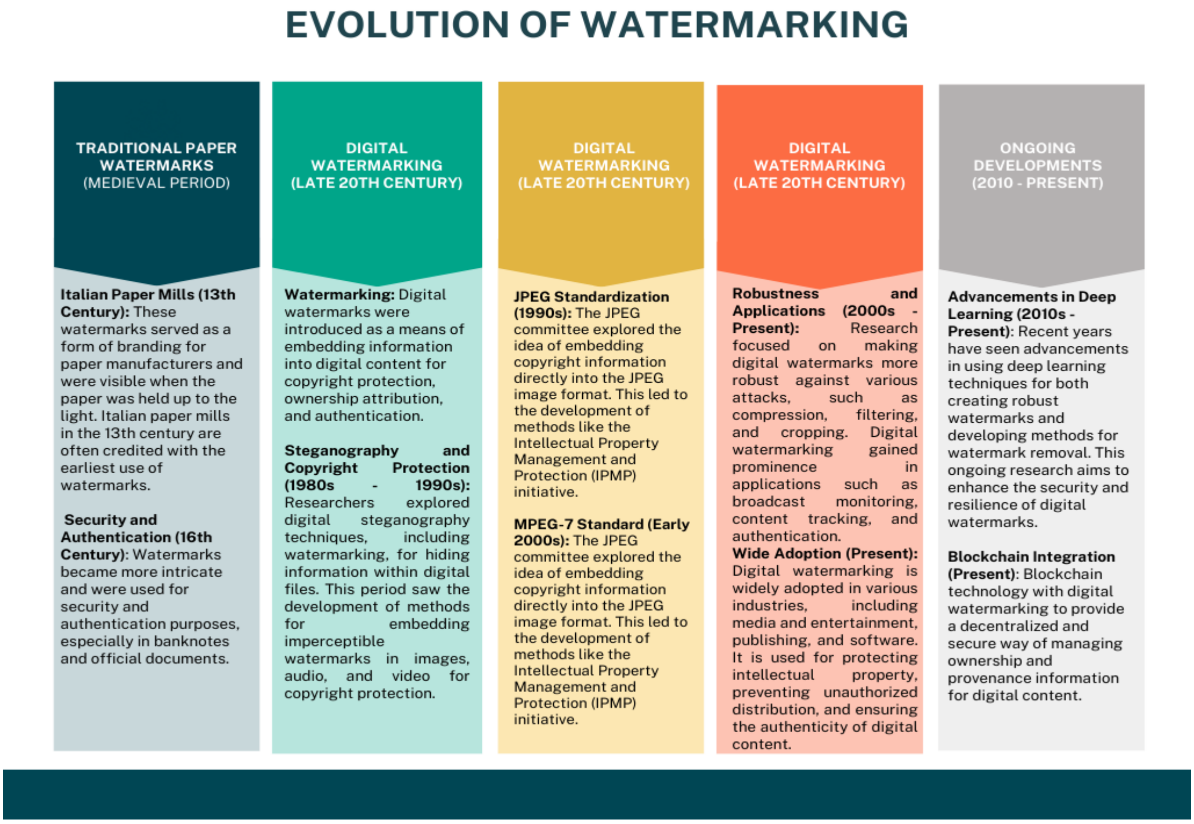

Figure 3: Evolution of watermarking system.

Figure 4: Types of attack

Table 2: Description of various kinds of hybrid attacks.

Hybrid Attack	**Description**	**Impact on Imperceptibility**	**Impact on Robustness**	**Impact on Capacity**	**Mitigation Strategies**
Compression and Noise Addition	Lossy compression followed by noise addition.	Moderate, compression may reduce quality, noise adds distortion.	High, compression reduces watermark data, noise distorts watermark.	Low, compression reduces capacity.	Redundant embedding, frequency domain techniques.
Cropping and Geometric	Cropping part of the image	Moderate, geometric	High, cropping and	Moderate, cropping	Adaptive watermarking

Transformations	followed by rotation, scaling, or translation.	changes may not be noticeable.	transformations can distort or remove watermark.	reduces image area for watermark.	, robust geometric transform techniques.
Filtering and Compression	Filtering operations followed by lossy compression.	Moderate, filtering smoothes image, compression reduces quality.	High, filtering removes high-frequency components, compression further reduces robustness.	Low, compression reduces capacity.	Frequency domain techniques, perceptual models.
Resampling and Histogram Equalization	Changing resolution followed by contrast enhancement.	Moderate, resampling and contrast changes may affect quality.	High, resampling alters pixel arrangement, equalization distorts intensity distribution.	Moderate, resampling changes image resolution.	Redundant embedding, adaptive watermarking.
Rotation and Recompression	Image rotation followed by lossy recompression.	Moderate, rotation might not affect perceived quality, recompression reduces quality.	High, rotation changes spatial orientation, recompression reduces data.	Low, recompression reduces capacity.	Robust geometric transform techniques, frequency domain techniques.
Noise Addition and Quantization	Adding noise followed by intensity level reduction.	High, noise and quantization degrade quality.	High, noise distorts pixel values, quantization reduces precision.	Moderate, quantization reduces data detail.	Redundant embedding, data compression techniques.
Geometric Transformations and Noise Addition	Scaling or rotation followed by noise addition.	Moderate, geometric changes and noise affect quality.	High, transformations alter spatial structure, noise degrades further.	Moderate, transformations and noise affect embedding.	Adaptive watermarking, robust geometric transform techniques.

2 TYPES OF MEDICAL IMAGE WATERMARKING

The various watermarking system used in medical images are depicted as below:

2.1 Spatial and transform domain in watermarking

Spatial domain techniques involve directly manipulating the pixel values of medical images to embed security features. Recent research has focused on enhancing the robustness and imperceptibility of these methods. **Robust LSB-Based Watermarking** approaches use error correction codes to enhance the robustness of LSB methods against common attacks while maintaining image quality [28]. **Adaptive ROI-based Watermarking t**echniques that adaptively select ROI and RONI to ensure that diagnostic regions remain unaltered while embedding watermarks in less critical areas. Transform domain techniques embed security features in the frequency components of medical images, offering improved robustness against attacks such as compression and noise [29]. **Hybrid DWT-DCT Methods c**ombining DWT and DCT to enhance both robustness and imperceptibility. These methods have shown improved performance in resisting a variety of attacks. **Enhanced DFT-Based Watermarking** proposed DFT methods that incorporate geometric correction algorithms to better withstand rotation and scaling attacks [30]. Table 3 describe the various techniques, advantages, disadvantages and applications used in a spatial and transform domain.

Table 3: Various aspects in spatial and transform domain

Aspect	**Spatial Domain**	**Transform Domain**
Description	Directly modifies the pixel values of the host image to embed the watermark.	Modifies the frequency coefficients of the image using transformations like DCT, DWT, or FFT to embed the watermark.
Techniques	**LSB e**mbeds watermark in the least significant bits of pixel values. **LSB Matching**: Improves robustness by randomly changing LSB bits.	**DCT:** Embeds watermark in the DCT coefficients. **DWT:** Uses wavelet coefficients. **FFT:** Embeds in the frequency domain.
Advantages	Easy to implement with low computational complexity. **Low Distortion**: Minimal changes to the original image.	**Robustness**: More robust against various type attacks like compression, filtering, and noise. **Perceptual Transparency**: Less visible alterations.
Disadvantages	**Low Robustness**: Vulnerable to attacks or manipilation like cropping, compression, and noise. **Perceptibility**: Changes can be more noticeable.	**Complex Implementation**: Requires more computational resources and complex algorithms.
Applications	**Low-security Needs**: Suitable for applications where high security is not critical (e.g., copyright notices).	**High-security Needs**: Suitable for secure applications like digital rights management, medical imaging, and confidential document protection.

2.2 Encryption and Compression techniques in watermarking

Compression techniques aim to reduce the size of medical images for efficient storage and transmission while preserving image quality and enabling secure data embedding. **Lossless Compression with Embedded Watermarking t**echniques that integrate lossless compression algorithms with watermarking, ensuring no loss of diagnostic information while embedding security features [52]. **Adaptive Compression Algorithms** proposed methods that adjust compression levels based on the content of the image to optimize the balance between compression efficiency and watermark robustness

[53]. Encryption converts medical images into an unreadable format to protect against unauthorized access during storage and transmission. **Lightweight Encryption Schemes** proposed a encryption algorithms that require less computational power, making them suitable for real-time applications and resource-constrained environments such as mobile health devices [54]. **Homomorphic Encryption** which allows computations to be performed on encrypted data without decrypting it first, enabling secure processing of medical images in cloud environments [55]. Table 4 describes the various approaches for encryption and compression techniques used in watermarking system.

Table 4: Different approaches for encryption and compression technique

Aspects	Details
Encryption in Watermarking	**Purpose**: Protects watermark from unauthorized access and manipulation. **Techniques**: Symmetric (e.g., AES), Asymmetric (e.g., RSA), Chaotic.
Compression in Watermarking	**Purpose**: Reduces size of watermarked image for easier storage and transmission. **Techniques**: Lossless (e.g., PNG), Lossy (e.g., JPEG).
Integration Approaches	**Pre-Watermarking Encryption**: Encrypt image before embedding watermark. **Post-Watermarking Encryption**: Embed watermark first, then encrypt. **Compression After Watermarking**: Compress watermarked image for reduced size. **Compression Before Watermarking**: Compress image before watermarking.
Common Techniques	**DCT/DWT**: Used for efficient representation of image data, making watermark resistant to attacks. **Hybrid**: Combining DCT/DWT with encryption (e.g., AES, chaotic).
Applications	**Medical Imaging**: Secures patient data with efficient transmission. **Digital Media Protection**: Protects intellectual property rights. **Secure Communications**: Ensures transmitted images are compressed and encrypted.
Challenges	**Balancing Compression and Quality**: Ensuring compression doesn't degrade image quality or watermark. **Encryption Overhead**: Managing computational complexity.

2.3 Optimization techniques in watermarking

This research explores the optimization of CNNs for lung cancer classification. By employing hyper parameter optimization and advanced image pre-processing, the study demonstrates enhanced model performance across diverse datasets. This improvement highlights better generalizability and interpretability, making it a significant step forward in the use of AI for lung cancer diagnostics[49]. This study introduces a novel approach combining PSO with HE for medical image segmentation. The optimization technique significantly improves accuracy, precision, recall, and F1-score compared to traditional methods like Otsu and Watershed. This approach proves particularly effective in enhancing the segmentation quality of lung CT scans and chest X-rays, crucial for early disease detection and treatment planning [50]. This research presents an improved U-Net architecture that integrates HDC modules. The technique addresses the challenge of capturing fine details and edge information in brain tumour images. By using an encoding-decoding structure, the method significantly increases segmentation accuracy, making it a valuable tool for precise tumour identification and treatment planning [51]. Table 5 define the source used in optimization methods and Figure 5 defines different approaches in watermarking with optimization.

Table 5: Different aspect used in Optimization techniques.

Aspect	Description
Deep Learning and AI Integration	CNNs: Used for segmentation, classification, and detection, reducing manual feature extraction. GANs: Enhance image resolution and quality. RNNs: Applied in tasks requiring temporal information.
Fast Imaging Techniques	Advanced Image Reconstruction: CT, CBCT, and multi-spectral CT improve speed and quality of imaging. AI-Powered Imaging: Enhances processes in PET and MRI.
Clinical Decision Support	AI tools like Black ford, Viz.ai, and Zebra Medical Vision assist in detecting abnormalities and clinical decision-making.
Cloud-Based and Mobile Imaging	Mobile CT/MRI Units: Provide imaging services in remote areas. Cloud Solutions: Amazon's Health Lake Imaging for managing large imaging data.
Emerging Technologies	Hyper spectral Imaging: Offers detailed diagnostic information. Molecular Imaging: Improves accuracy in disease detection and treatment planning.

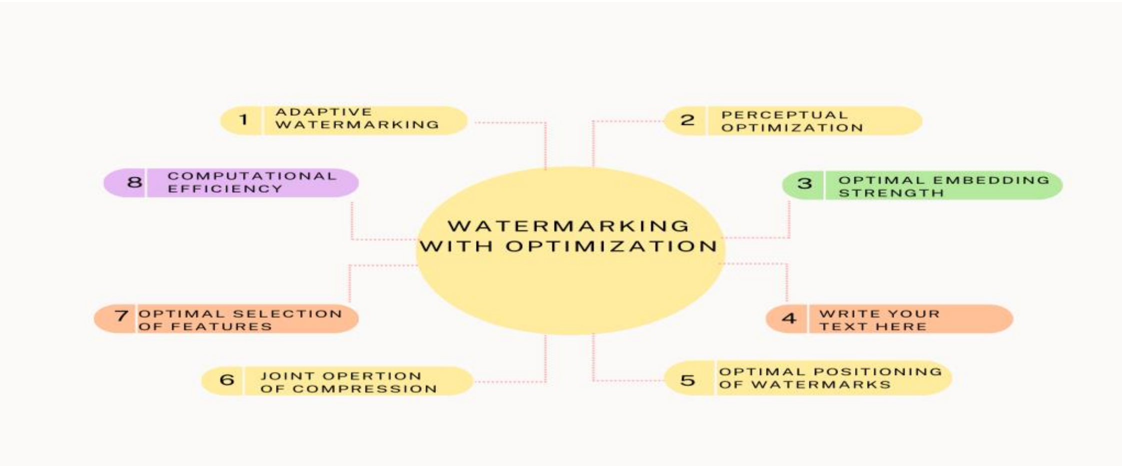

Figure 5: Different approaches in watermarking with optimization

2.4 ML and DL algorithms in watermarking

ML and DL algorithms have been employed to detect and diagnose diseases from medical images with high accuracy, often surpassing human experts. **CNNs** have been widely used for detecting diseases such as cancer, diabetic retinopathy, and pneumonia from medical images. A CNN model was developed [39], outperformed radiologists in breast cancer detection using mammograms. **Transfer Learning** techniques, where pre-trained models on large datasets are fine-tuned on medical imaging datasets, have shown great promise in improving diagnostic accuracy with limited data. In [40], utilized transfer learning to enhance the performance of a DL model for detecting lung diseases from chest X-rays. Image segmentation is critical for delineating anatomical structures and regions of interest in medical images, aiding in diagnosis, treatment planning, and monitoring. **U-Net Architecture**, a popular DL architecture for biomedical image segmentation, has been widely adopted and improved upon for various applications, including brain tumour segmentation and organ delineation. U-Net [41], was presented and automated framework that adapts the U-Net to different segmentation tasks, achieving state-of-the-art results in multiple benchmarks. **3D Segmentation Models:** Advances in 3D CNNs have enabled the segmentation of volumetric medical images, providing more accurate and detailed anatomical structures. In [42], introduced the V-Net, a 3D CNN for volumetric medical image segmentation, which has been highly effective for tasks such as prostate segmentation in MRI scans. Classification tasks involve assigning labels to medical images or regions within images to identify the presence or stage of a disease. **Multi-Task Learning:** Multi-task learning approaches train models to perform several related tasks simultaneously, improving generalization and performance on individual tasks. The [43], demonstrated that multi-task learning models can classify multiple diseases from chest X-rays more accurately than single-task models. Explainable AI which efforts to make DL models more interpretable have led to the development of techniques that provide insights into model decisions, crucial for clinical acceptance. The author [44], reviewed methods for explainable AI in medical imaging, highlighting approaches like attention mechanisms and saliency maps that help clinicians understand model predictions. Predictive models use medical images to forecast disease progression, treatment response, and patient outcomes, enabling personalized medicine. **Radiomics** involves extracting quantitative features from medical images and using ML models to predict outcomes such as survival rates and treatment response. They developed [45], radiomic models that predict overall survival in lung cancer patients based on CT scan features. **Temporal Models:** RNNs and LSTM networks are used to model temporal dependencies in longitudinal imaging data, improving predictions of disease progression. In [46], employed an RNN-based model to predict Alzheimer's disease progression from sequential MRI scans. Enhancing Image Quality and Reconstruction in ML and DL techniques have been applied to improve the quality and resolution of medical images, as well as to reconstruct images from incomplete or corrupted data. **Super-Resolution** DL-based super-resolution models enhance the resolution of medical images, aiding in better visualization and diagnosis. The author proposed [47], a DL method for super-resolving low-resolution MRI images, significantly improving image quality. **Noise Reduction:** Denoising algorithms based on DL can effectively reduce noise in medical images, enhancing clarity without compromising diagnostic information. A CNN-based [48], denoising algorithm that improved the quality of low-dose CT images. Table 6 discusses about the ML and DL techniques used in watermarking system.

Table 6: Elaborate the ML and DL techniques used in watermarking system.

Category	**Aspect**	**Description**	**Techniques and Models**
Disease Detection and Diagnosis	High Accuracy	ML and DL algorithms detect and diagnose diseases from medical images with high accuracy, often surpassing human experts.	CNNs
Image Segmentation	Delineating Structures	Critical for identifying anatomical structures and regions of interest, aiding in diagnosis and treatment planning.	U-Net Architecture
3D Segmentation Models	Volumetric Imaging	Segmentation of volumetric medical images provides detailed	V-Net (3D CNN)

		anatomical structures.	
Image Quality Enhancement	Improving Resolution	Techniques to improve the quality and resolution of medical images.	Super-Resolution, Denoising
Explainable AI	Model Interpretability	Efforts to make DL models more interpretable to gain clinical acceptance.	Attention Mechanisms, Saliency Maps
Predictive Models	Forecasting	Using medical images to predict disease progression, treatment response, and patient outcomes.	Radiomics, Temporal Models

2.5 Biometric Techniques in watermarking

Biometric techniques use unique biological traits to authenticate users and control access to medical images [8]. Multimodal Biometrics which combining multiple biometric traits (e.g., fingerprint and iris recognition) to enhance security and reduce false acceptance rates. Biometric Encryption which Integrating biometric authentication with encryption algorithms to provide an additional layer of security. Multimodal Biometrics for Medical Images. Enhancing Security and Reducing False Acceptance Rates for combining Fingerprint and Iris Recognition which captures unique patterns of ridges and valleys on a person's finger. It is widely used due to its ease of capture and uniqueness and Iris Recognition uses the unique patterns in the colored part of the eye, offering high accuracy and reliability. The benefits are improved Accuracy by combining these two modalities ensures higher accuracy since both must match for access to be granted and increased security which is more challenging for unauthorized users to replicate several biometric traits [12]. Biometric Encryption for Medical Images Integrating Biometric Authentication with Encryption to Secure Key Generation which biometric data, such as fingerprints or iris patterns, are used to generate unique cryptographic keys. These keys can be regenerated only when the correct biometric input is presented, ensuring that the data remains secure even if the biometric template is intercepted. Template Protection of the raw biometric data is transformed and stored securely, protecting it from being exposed or tampered with. Enhanced Privacy for biometric encryption ensures that even if the biometric data is compromised, it cannot be used without the corresponding cryptographic key. Applications in Medical Imaging Secure Access Control for Only authorized personnel can access medical images, ensuring that patient data remains confidential. Audit Trails and Accountability for biometric authentication provides a reliable method to track access and modifications to medical images, enhancing accountability. Integration with PACS can integrate biometric authentication to control access to stored medical images [17]. Table 7 describes the biometric methods such as multimodal biometrics and biometric encryption in watermarking system.

Table 7: Biometric techniques in watermarking system

Category	Aspect	Multimodal Biometrics	Biometric Encryption
Objective		Combine multiple biometric traits for authentication	Integrate biometric data with encryption algorithms
Techniques	Biometric Modalities	Fingerprint and Iris Recognition	Secure Key Generation using Biometric Traits
		Face and Voice Recognition	Template Protection
Applications	Medical Image	Enhance security by requiring	Use biometric traits to generate

	Access	multiple biometric traits for access	cryptographic keys for secure access
	PACS Integration	Control access to Picture Archiving and Communication Systems	Encrypt medical images using biometric-generated keys
Challenges	Complexity	Implementation complexity due to the need for multiple biometric sensors	High computational cost for generating and managing encryption keys
	User Acceptance	Potential user resistance to providing multiple biometrics	User inconvenience if biometric data is needed frequently for key generation
	Performance	May require more processing time due to multiple trait analysis	Possible performance issues due to the complexity of encryption algorithm

2.6 Blockchain in watermarking

Data Security in blockchain ensures the security and integrity of medical images by providing a tamper-proof ledger for storing image metadata and access logs. **Immutable Storage** nature ensures that once medical image data is recorded, it cannot be altered or deleted, protecting against unauthorized modifications. In [31], developed a blockchain-based framework for secure storage and sharing of medical images, ensuring data integrity through cryptographic hashing. Smart contracts on the blockchain can automate and enforce access control policies, ensuring that only authorized individuals can access medical images. The proposed [32], a blockchain-based access control system for medical images, leveraging smart contracts to manage permissions and audit access logs. Privacy in Blockchain can enhance patient privacy by providing secure and transparent mechanisms for consent management and data access. **Patient-Centric Models** in blockchain enables patients to have greater control over their medical images, allowing them to grant and revoke access as needed. In [33], introduced a patient-centric blockchain model for managing access to medical images, where patients can control who views their data. **Privacy-Preserving Techniques:** Advanced cryptographic techniques, such as zero-knowledge proofs, can be integrated with blockchain to enhance privacy while maintaining data utility. The author explored [53,34], the use of zero-knowledge proofs in blockchain systems to enable privacy-preserving medical image sharing. Interoperability in blockchain can facilitate interoperability between different healthcare systems by providing a unified, decentralized platform for data exchange. **Standardized Protocols:** Blockchain can use standardized protocols for recording and sharing medical images, promoting interoperability between disparate systems. In [35], a method of blockchain-based interoperability framework for medical imaging, utilizing standardized data formats to ensure seamless data exchange. **Cross-Institutional Data Sharing** in bockchain enables secure and efficient sharing of medical images across different healthcare institutions, improving collaboration and continuity of care. In [36], developed a blockchain-based system for cross-institutional sharing of medical images, enhancing collaboration between hospitals and research institutions. Trust and Transparency in blockchain enhances trust and transparency in medical imaging by providing an auditable and transparent record of all transactions and data access. **Audit Trails** in blockchain provides a transparent and immutable audit trail for all interactions with medical images, facilitating accountability and trust.

[37], implemented a blockchain-based audit trail system for medical images, allowing stakeholders to verify data provenance and integrity. **Trustworthy AI Models** in blockchain can be used to ensure the integrity and trustworthiness of AI models used in medical imaging by recording model training and validation data. A blockchain framework [38], to ensure the transparency and integrity of AI models in medical imaging, recording model updates and performance metrics on the blockchain. Table 8 discusses about the techniques and models with description in blockchain watermarking system. Various other techniques, including steganography**,** reversible data hiding, and chaotic encryption, offer additional layers of security for medical images. **Reversible Data Hiding in Encrypted Images techniques** that allow for the original image to be perfectly restored after the extraction of hidden data, ensuring no loss of diagnostic information. **Chaotic encryption Methods** which Utilizes chaotic systems to create highly secure and complex encryption schemes for medical images .

Table 8: The techniques and models with description in blockchain watermarking system

Category	**Aspect**	**Description**	**Techniques and Models**
Data Security	**Immutable Storage**	Ensures that medical image data, once recorded, cannot be altered or deleted, protecting against unauthorized modifications.	Cryptographic Hashing
	Access Control	Smart contracts automate and enforce access control policies, ensuring only authorized individuals can access medical images.	Smart Contracts
Privacy	**Patient-Centric Models**	Enables patients to control access to their medical images, allowing them to grant and revoke access as needed.	Patient-Centric Blockchain Models
	Privacy-Preserving Techniques	Advanced cryptographic techniques like zero-knowledge proofs enhance privacy while maintaining data utility.	Zero-Knowledge Proofs
Interoperability	**Standardized Protocols**	Blockchain uses standardized protocols for recording and sharing medical images, promoting interoperability between disparate systems.	Standardized Data Formats
	Cross-Institutional Data Sharing	Enables secure and efficient sharing of medical images across different healthcare institutions, improving collaboration and continuity of care.	Cross-Institutional Blockchain Systems

Trust and Transparency	**Audit Trails**	Provides a transparent and immutable audit trail for all interactions with medical images, facilitating accountability and trust.	Blockchain-Based Audit Trails
	Trustworthy AI Models	Ensures the integrity and trustworthiness of AI models used in medical imaging by recording model training and validation data.	Blockchain Framework for AI Models

3 Basic framework of a digital image watermarking system

Digital watermarking is a technique used to conceal data within digital media. The watermark is embedded in such a way that it remains imperceptible, allowing for subsequent identification and verification of the data.

3.1 Basic components of watermarking system

Various watermarking approaches typically consist of three fundamental components.

a) Generation of watermark: The creation of a watermark varies depending on the application's specific requirements and objectives. Figure 5 illustrates the watermark generation process.

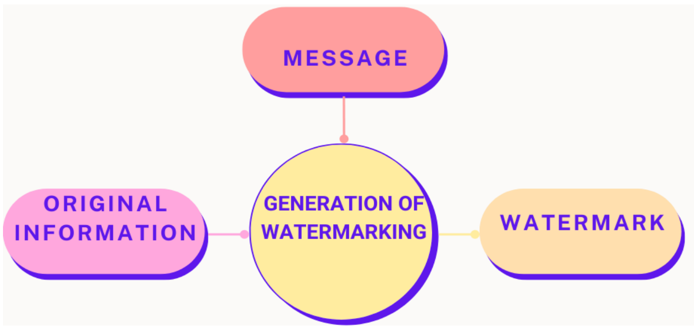

Figure-5: Generation of watermarking system

b) Hiding of watermark: After the watermark is generated, it is embedded into the host image using a data hiding key to produce the watermarked image. Figure 6 outlines the process of embedding the watermark.

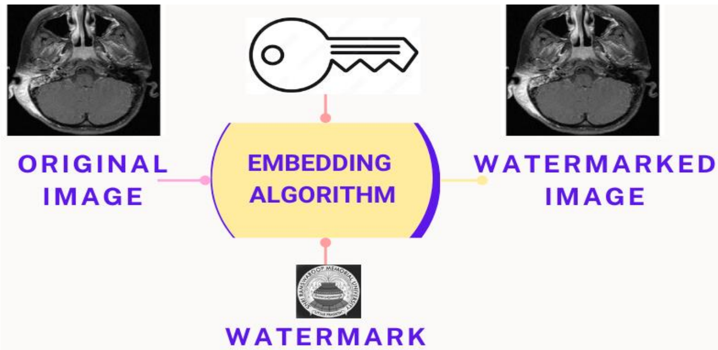

Figure-6: Process of embedding in watermarking

c) Extraction of watermark: Upon receiving the watermarked image, the extraction process involves using a reverse information-hiding algorithm along with the key to retrieve the embedded watermark. Figure 7 illustrates the watermark extraction process.

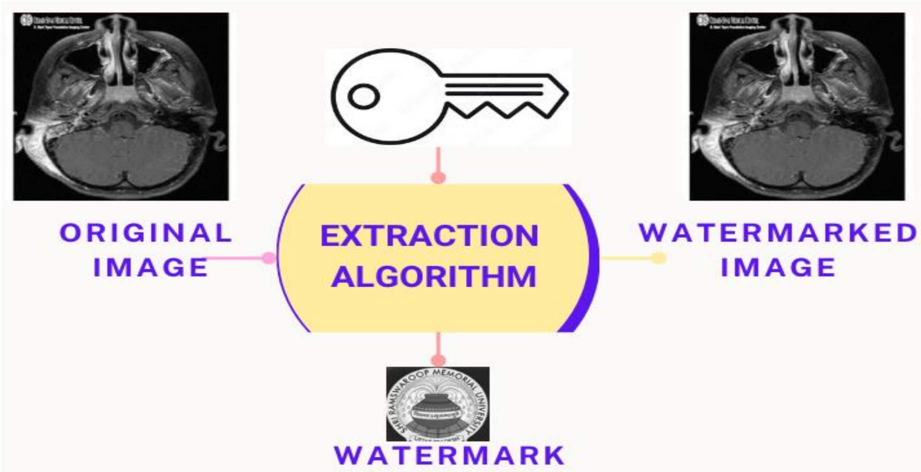

Figure-7: Process of extraction in watermarking

3.2 Basic components of medical image watermarking system

Medical imaging techniques like MRI, CT scans, X-rays, and others are essential for improving healthcare by aiding in accurate diagnosis. These methods are tailored to meet individual patient needs, providing crucial data that doctors rely on for effective medical assessments. Figure 8 illustrates the components of medical image watermarking systems. These components often include:

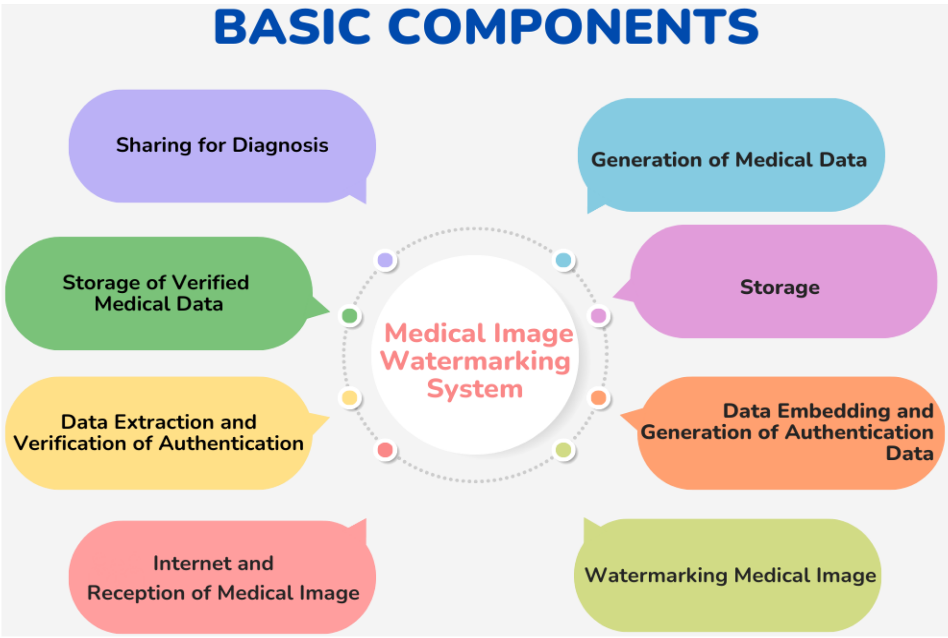

Figure-8: Basic components of medical image watermarking system

(d) Storage of medical images: The creation of medical images, it is essential to securely store them.

(e) Data embedding and authentication information generation: EDHI and authentication data are simultaneously embedded into the medical image. This process results in a watermarked medical image that facilitates authentication before diagnosis.

(f) Communication networks: The watermarked medical image is transmitted over insecure communication networks to enable remote consultation with doctors or for obtaining a second opinion.
(g) Receipt of medical image: The medical image transmitted over communication networks is received on various devices such as personal computers, smart phones, etc.

4 Evaluation of Watermarked Medical Images

In the context of medical images, PSNR, SSIM, and MSE play crucial roles in assessing the quality and fidelity of images, especially when they are watermarked or processed in some way.

4.1 Performance Metrics for the watermarking process

Various metrics such as PSNR, MSE, and SSIM are used to quantify the distortion between the original image O of size P X Q and its watermarked counterpart OW. These metrics play a crucial role in evaluating how well the watermarking process preserves image quality and integrity. Table 9 shows the role and their contributions:

Table 9: Role and their contributions of various performance metrics:

Metric	Role	Formula
Peak Signal-to-Noise Ratio (PSNR)	Measures fidelity by quantifying signal-to-noise ratio. Higher values indicate better image quality.	$\mathrm{PSNR} = 10 \cdot \log_{10}\left(\frac{\mathrm{MAX}^2}{\mathrm{MSE}}\right)$, where MAX is the maximum possible pixel value (e.g., 255 for 8-bit images), and MSE is Mean Squared Error.
Structural Similarity Index (SSIM)	Evaluates similarity between two images based on luminance, contrast, and structure.	$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)}$, where μ denotes mean, σ denotes variance, σ_{xy} denotes covariance, and C_1, C_2 are constants to stabilize the division.
Mean Squared Error (MSE)	Measures the average squared difference between original and reconstructed (or watermarked) images.	$\mathrm{MSE} = \frac{1}{PQ}\sum_{k=0}^{P-1}\sum_{l=0}^{Q-1}(O(k,l) - OW(k,l))^2$, where O is the original image, OW is the watermarked image, P and Q are dimensions of the images.

These metrics collectively help in evaluating the trade-offs between imperceptibility (how well the watermark is hidden), fidelity (how accurately the original image is preserved), and robustness (how well the watermark survives various attacks or processing steps). In medical applications, maintaining high image quality while ensuring the presence and detect ability of watermarks is crucial for both diagnostic reliability and data integrity in clinical settings.

4.2 Performance Metrics for the Extraction process

To validate extracted watermarks, metrics such as CR, BER, and AR are employed:
CR: Compression ratio analyze the similarity between embedded LL and extracted L'L'.
BER: Measures errors in the extraction of binary sequences.
AR: Calculates the correctness of extracted binary data.

4.3 Evaluation of Embedding Capacity

Embedding capacity assesses the maximum amount of binary data that can be embedded using a specific algorithm:

EC = Number of binary bits /Number of pixels in medical image

This formula represents the ratio of the number of binary bits that can be embedded per pixel in a medical image, providing a measure of how much data can be hidden within the image.

4.4 False Positive and False Negative Evaluation Rates

In watermarking for authentication, False Positive Rate, False Negative Rate and Tamper Detection Rate evaluate the accuracy of detecting tampering in images.

5 Challenges and Considerations

Medical image watermarking is used in various watermarking techniques and Figure 9 depicts the various challenges faced in medical image watermarking system.

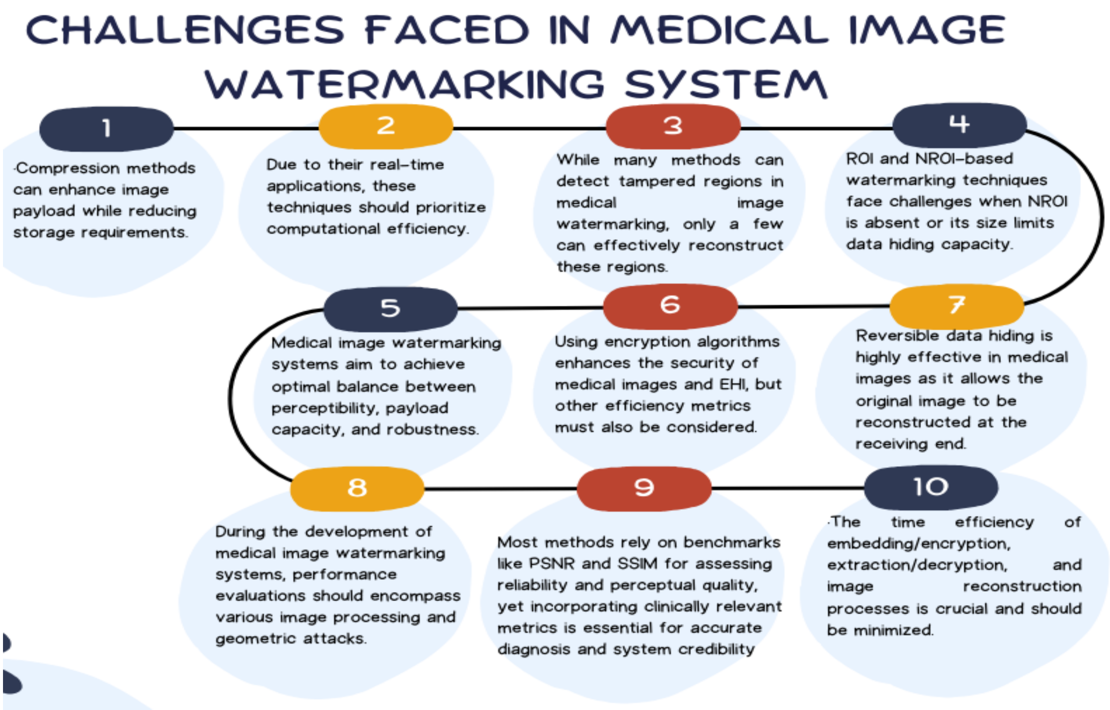

Figure-9: Challenges faced in medical image watermarking system.

6. Conclusions

Medical image watermarking is an emerging technology in the present world and has the latency to provide an appreciable solution for various applications of telemedicine, electronic health records, medical research and clinical diagnostics. The challenges to ensuring watermarked image comply with medical imaging standards, include confidentiality and the prevention of manipulations and trust may be built in the e-healthcare system. Several medical image watermarking techniques have been developed in different domains with a different applicability. This paper presents critical review of various medical image watermarking techniques using spatial and transform domain, encryption and compression techniques in watermarking, optimization techniques in watermarking, ML and DL algorithms in watermarking, biometric techniques in watermarking, blockchain in watermarking, novel application and characteristics. We believe that, this survey is to help future researchers to provide a valuable source of medical image watermarking information that might address the potential issues and challenges in e-healthcare setups.

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