www.ijonest.net

Advancing Image Database Technologies in Clinical Decision Support Systems: A Systematic Literature Review

Ruizhi Yu
University of Nevada Las Vegas, United States

Yubo Fu
Colorado State University Pueblo, United States

To cite this article:

Yu, R. & Fu, Y. (2024). Advancing image database technologies in clinical decision support systems: A systematic literature review. *International Journal on Engineering, Science, and Technology (IJonEST), 6*(2), 132-145. https://doi.org/10.46328/ijonest.202

International Journal on Engineering, Science, and Technology
2024, Vol. 6, No. 2, 132-145 https://doi.org/10.46328/ijonest.202

Advancing Image Database Technologies in Clinical Decision Support Systems: A Systematic Literature Review

Ruizhi Yu, Yubo Fu

Article Info

Article History

Received:
10 September 2023
Accepted:
19 November 2023

Keywords

Image database technology
Clinical decision support system
Information retrieval from image
Image database management
Database system for medical imaging

Abstract

Image data has played a crucial role in the Clinical Decision Support System (CDSS). While numerous studies have focused on developing techniques to extract valuable information from image data to aid in disease diagnosis, there is a lack of attention on the storage and retrieval technologies for image database. Extracting information from image data for decision making models requires a substantial volume of image data. However, images often come with large file sizes due to their high resolution and complex details, and compressing such data may lead to the loss of critical diagnostic information. Thus, the challenge lies in preserving the relevant information within images while managing data volume. This literature review aims to explore existing research on image-specific database systems, and their techniques for image data storage and information retrieval to enhance the application of images within CDSS. The review also brings attention to the need for specialized database systems that are tailored to handle the unique characteristics of clinical image data. Consequently, this review serves as a foundation for future research endeavors aimed at advancing image data management and utilization in the realm of medical diagnosis and beyond.

Introduction

Computerized Clinical Decision Support Systems (CDSSs) are software programs designed to assist clinic decision-making by using data, medical knowledge, and analysis engine for generating patient-specific assessments or recommendations to health professionals (Sim et al., 2001). It either retrieves data to evaluate a set of literature-based, practice-based, or patient-directed rules from a prepopulated knowledge base, or leverages artificial intelligence, machine learning, or other statistical learning methods to produce recommendations (Berner, 2007). The traditional information includes patient's historical records like Electronic Health Records (EHR) (HealthIT, 2018; Lopez et al., 2023). In contrast, contemporary data sources incorporate some unstructured data types, such as images, audio, and other forms of multimedia content. While CDSSs primarily rely on structured medical data and clinical knowledge, the heterogenous image data has significantly expanded their scope and effectiveness (Georgiou et al., 2011). The importance of image data in CDSS is evident in various medical domains, including radiology, pathology, and cardiology. The fusion of clinical and imaging data leverages the power of artificial intelligence and machine learning to assist healthcare professionals in identifying patterns, anomalies, and potential risk factors, leading to improved diagnostic accuracy, better treatment selection, and ultimately, enhanced patient outcomes (Sutton et al., 2020).

With the increasing prevalence of image applications, there are more requirements for advanced technologies of information retrieval from images, as well as image storage and processing (Hill et al., 2001). Numerous advanced image analysis techniques are now available to aid healthcare professionals or users in extracting information from images or facilitating image classification, including but not limited to tumor detection, medical image interpretation, diagnosis of diabetic retinopathy, and the development of diagnostic tools utilizing multimodal feature learning for Alzheimer's disease diagnosis (Georgiou et al., 2011). However, there are few articles dedicated to the technology of image databases, primarily due to their limited utilization within the CDSS. As a decision support system, researchers have predominantly focused on the inferences that can be drawn from the data, without delving into the origins of the data itself. While many studies have delved into the storage of images in an image database (Chang et al., 1988), many modern technologies necessitate databases to possess functionalities beyond mere image storage. For example, telemedical communication requires rapid retrieval of images or image-related information from the database for real-time interactions (Cao et al., 2003). Currently, the literature is scarce on comprehensively summarizing the image database functionalities aligned with modern CDSS requirements and the corresponding technologies. This leads to two research questions: What are required functionalities for Image Database? And what are current technologies?

Another issue that researchers have overlooked is the impact of data storage on the performance of CDSS systems. This is primarily due to the lack of quality attributes for image database implementation in CDSS. Quality attributes are crucial for the process of system development, as they define the criteria for requirements that subsequently guide design, implementation, and testing activities (Bass et al., 2003). System quality and associated quality attributes are inherently domain specific (DeLone et al., 2003). To the best of our knowledge, no research has identified the desired quality attributes. Thus, this leads to our third research question: what are the quality attributes of image database implementation in CDSS? These three research questions naturally lead to the need for a systematic literature review (SLR) of literature about image database implementation in CDSS, because it provides "a means of evaluating and interpreting all available research relevant to a particular research question or topic area or phenomenon of interest" (Kitchenham, 2004). The next section of this SLR represents the methods and the final two sections represent the results and discussions.

Method

This systematic literature review adheres to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) checklist and reporting workflow, in accordance with the guidelines outlined by Page et al. (2021), as delineated below.

Eligibility Criteria

This review includes all peer-reviewed studies that examined image database systems. Inclusion criteria define English as the only acceptable language. Additionally, each study has to be required to provide information regarding at least one system functionality in conjunction with the associated image database technology. Moreover, studies have to address the quality attributes or evaluation criteria related to the technology. An overview of the eligibility criteria is presented in Table 1.

Table 1. Eligibility Criteria

	Specified Criteria
Inclusion	Peer reviewed studies
	Studies reported implementation of image database system
	Studies reported at one functionality, related technology and quality attribute
Exclusion	Studies published in a language other than English
	Studies reported image database system other than health domains
	Studies reported image database system without specific functionality
	Systematic reviewed studies of image database system
	Adoption studies of image database system

Information Source and Search Strategy

The information search sources used for this review include PubMed, IEEE, Science Direct, ACM Digital Library, and Wiley Online Library. In addition to these databases, backward-reference list checking was performed to identify additional studies. The following combination of keywords were used: *(“clinical decision support system”* OR *“medical imaging”*) AND (*“image database”* OR *“image database system”* OR *“Picture Archiving and Communication System”*).

Selection Process

The selection process of studies retrieved from the initial search included three iterative phases: (1) screening phase, where titles, abstracts, and keywords of articles were reviewed to exclude irrelevant ones based on the eligibility criteria; (2) eligibility phase, where the full-text of articles were reviewed to assess their relevance to this study; and (3) backward-reference list checking, where phases 2 and 3 were repeated for eligible articles from phase 2.

Data Collection Process and Data Items

A data extraction form was created (see Table 2) based on research questions. The functionalities of image database systems were firstly extracted. The SLR summarized all image database systems with their functionalities and required technologies, as well as quality attributes if they can guide the design, implementation, and test of image database systems. It also reviewed how studies evaluated the performance of functionalities in image database systems based on quality attributes. At last, the SLR also presented recommendations for future research, specifically focusing on investigating which technologies can simultaneously fulfill functionality requirements while ensuring Quality attributes.

Table 2. Data Extraction Form

Items	Descriptions
Functionalities	What are the required basic functionalities in an image database system implemented in the CDSS?
Technologies	What are current technologies that can fulfill those functionalities?
Quality Attributes	What are quality attributes that have been considered for guiding the design, implementation, and test of image database systems?

Critical Appraisal

Following the preliminary screening, two researchers independently undertook the second and third phases of the selection process. In cases of disagreement, extensive discussions were held among the researchers to reach a consensus. Subsequently, the selected articles were individually coded by the researchers, guided by the data extraction form. The following section provides the discussion of results.

Results

The initial database search yielded a total of articles. The review of title, abstract, and keywords excluded articles. Language criteria excluded four articles reported in a non-English language. After the full-text review, only the papers meeting the specified criteria were selected (see Figure 1). The final included articles are listed in Table 3.

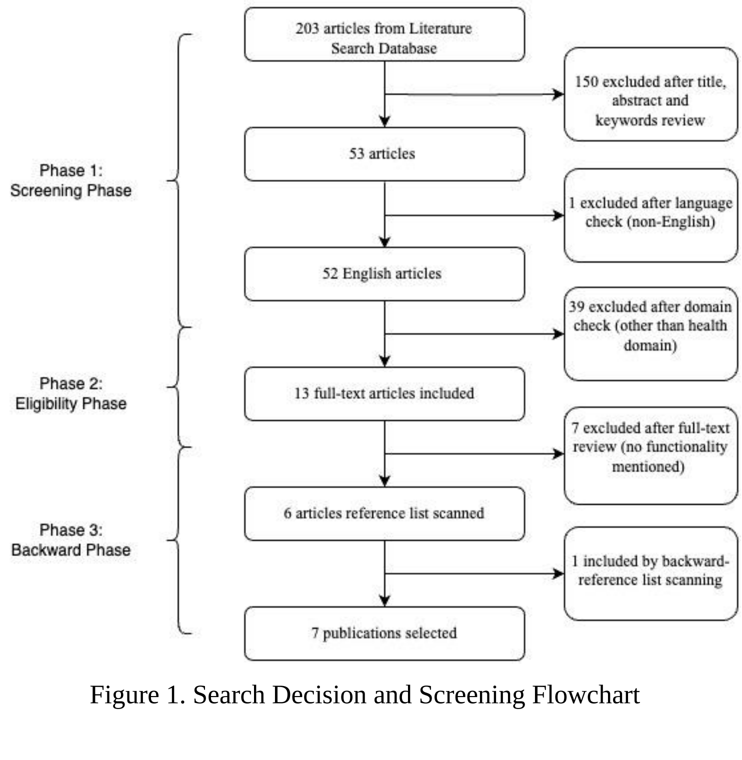

Figure 1. Search Decision and Screening Flowchart

Table 3. Final Included Articles

Index	Article	Artifact
1	(Cao et al., 2003)	An Integrated Medical Image Database
2	(Elbers et al., 2020)	An Imaging Research Database
3	(Santos et al., 2020)	Medical Imaging Repositories
4	(Siadat et al., 2005)	Human Brain Image Database System
5	(Marcos et al., 2007)	Medical Image Management
6	(Zhuang et al., 2023)	Lung CT Image Database
7	(Suapang et al., 2011)	Web-Based Medical Image Archiving and Communication System

Functionality

Similar to traditional databases, image databases possess certain essential functionalities, including data storage, information retrieval, and data security. More specifically, there are some functionalities unique to image databases, such as key point localization within images and image feature extraction (Siadat et al., 2005).

Data Storage

Image data differs from conventional structured or textual data in that it can occupy a significant amount of space, particularly as image resolutions continue to increase, leading to the continuous increase of image size in the health domain (Cao et al., 2003). The most common method of image storage is to save the original images on cloud drives or local hard disks, while keeping the image information in the traditional database with a specific format, such as DICOM (Elbers et al., 2020). This method preserves the size and quality of the original image, as well as providing timely access of image for stakeholders. However, this method has scalability limitations. Once the storage capacity reaches its limit, the cost will increase by expanding the storage size (Bhaya et al., 2021). Despite the efficiency achieved in information provision and image access, it is still a time-consuming process when dealing with certain real-time healthcare services, such as telemedicine systems (Cao et al., 2003).

The second method is image compression, which has proven to be a solution to reduce the size of a digital image file while attempting to maintain its visual quality and the information it contains (Cai et al., 2000). Image compression can occupy less storage space by reducing file size. It can also speed up image access within the database through reduced network congestion and faster content delivery due to less bandwidth requirement when transmitted over the internet or downloaded from a webpage (Siadat et al., 2005). However, image compression entails a loss of image quality, specifically the loss of some fine details, which are irreversible (Suapang et al., 2011; Cai et al., 2000). The detail loss is unacceptable for medical imaging, which demands a high level of precision, particularly when they are supporting the diagnosis and treatment (Gordillo et al., 2013).

The last method is to format the image into a 2D string with different structures, typically vector-oriented and pixel-oriented. This allows all image information to be stored in the form of strings within the database, thereby avoiding the storage demands associated with image formats while preserving all relevant information (Chang et al., 1988). However, this function has not been widely applied in the health domain, mainly because it relies on the accuracy of image processing. Any inaccuracies in the information conversion process have potential to mislead healthcare professionals when making decisions. Additionally, doctors are unable to access the correct information by viewing the original images if such errors have occurred.

Information Retrieval

Information retrieval is a critical aspect of contemporary image database technology. Traditional image information retrieval methods include various methods that are similar to query in relational database queries (Chang et al., 1988). Currently, the comprehensive medical image database system integrates web application servers, which are more user-friendly for stakeholders to access the image and require information more cost-effectively (Cao et al., 2003). Localization and feature extraction are two steps for information retrieval in integrated systems. Localization identifies and delineates the boundaries of anatomical structures within the image by strategically positioning an initial polygon around the interest area (Siadat et al., 2005).

The polygon serves as the foundation for subsequent analysis, particularly the application of deformable models, which allows for the creation of highly accurate and high-resolution segmentations. Following the precise localization, feature extraction identifies and extracts meaningful features from images to help stakeholders understand the anatomical context and support their semantically rich content-based procedures (Siadat et al, 2005). As a result, the extracted features are contextually relevant to the specific structure of interest, leading to semantic richness and less noise or irrelevant information in subsequent analysis stages.

However, this approach is highly sensitive to initial conditions. It is only effective for single targets. When it comes to multi-target localization, it may be prone to errors due to noise sensitivity (Zhang et al., 2017). Such errors can also lead to information loss during the feature extraction process. Therefore, this method requires further validation.

Data Security and Privacy

Among the selected articles, data privacy has been mentioned multiple times with a consistent method, the de-identification, which is a process to reduce personal privacy risks by removing identifiers from health information of medical images, thereby supporting the secondary use of data for comparative effectiveness studies, policy assessments, life sciences research, and other endeavors (Elbers et al., 2020; OCR, 2023). There is an absence of discussions about enhancing the security of the image data itself due to mature security services provided by cloud drives or local hard disks. However, some medical images, such as certain facial surgery photos still contain sensitive patient information, so simple de-identification cannot eliminate the risk of patient information leakage. Therefore, we argue that the privacy and security of image data itself and its associated information need to be carefully considered.

Technology

The performance of these functionalities can be achieved through the utilization of various technologies. The desired functionality of the image database dictates the selection of appropriate technologies. This section aims to provide a detailed description of the various technologies available for the implementation of these functions.

Technologies for Storage

The Digital Imaging and Communications in Medicine (DICOM) is the most common technology used in the storage of image database systems. It stands as the established standard for the communication and management of medical imaging data and related information (Thomas et al., 1995). It facilitates interoperability among medical imaging devices and systems from diverse manufacturers by defining specific "Transfer Syntaxes", like JPEG (Joint Photographic Experts Group) and RLE (Run-Length Encoding), for image encoding and compression. Different transfer syntaxes can be used based on the specific requirements of the medical application, including endoscopic, pathologic, and radiological images, as well as electrocardiograms (ECGs) (Cao et al., 2023; Suspang et al., 2011).

On the other hand, the 2D string format has two primary structures: Vector-oriented and Pixel-oriented. Vector-oriented structure encapsulates the essential geometric information of an image through vectorization, followed by representing an image in a mathematical and vector-based format. It is often employed in applications where the focus is on capturing and preserving the vector-based information of images, such as in computer-aided design (CAD) or graphics applications (Siadat et al., 2005). In contrast, the Pixel-oriented structure encodes individual pixels of the image by assigning a specific value or character in the string and meticulously capturing the visual details and color information of the image (Chock et al., 1984). The Pixel-oriented structure is commonly employed in applications where the integrity and fidelity of the image data are paramount, such as medical imaging, where even the minutest details in radiological or clinical images are critical for accurate diagnoses. This method retains the original pixel-by-pixel information, making it suitable for situations where image quality and precision are of utmost importance.

Technologies for Information Retrieval

Query is a fundamental component of information retrieval technology, used for retrieving desired information from data storage. The goal of a query is to filter and retrieve data based on user-provided conditions or examples to obtain relevant results. Different query technologies employ distinct strategies and techniques to achieve this objective. Other than traditional query, general relational database systems also involve other advanced technologies like Query-by-Example (QBE) and quadtrees. QBE is a database querying method designed to simplify interaction between users and databases. In QBE, users do not need to write specific query languages or expressions; instead, they provide example data as query criteria used by the system to execute a database query and return results (Zloof et al., 1977). A quadtree is a common spatial partitioning data structure used for recursive partitioning and organization of two-dimensional planes by dividing them into four quadrants, each of which can be further subdivided into four sub-quadrants, creating a tree-like structure (Chang et al., 1979).

Due to the unique nature of image databases, general queries are typically limited to extracting information stored in the database. Therefore, image databases often require specialized indexing techniques. Iconic indexing is a technology employed for the retrieval and management of multimedia data, particularly concerning images and videos. It utilizes icons or representative images to describe entire multimedia files and enables users to obtain information about the content of the file by viewing the icons. The core concept behind iconic indexing is to map complex multimedia data onto easily understandable icons, thereby simplifying the retrieval process (Chang et al., 1988). Apache Lucene is a Java library widely employed for text search and indexing in various applications. In medical image processing and retrieval, Lucene can be used for two types of data indexing: Full Text Indexing and Metadata Indexing (Santos et al., 2022). The image database system can create a full-text index of text data related to images, such as image descriptions and case information, to enable users to search medical image databases through text queries. In terms of Metadata Indexing, DICOM metadata contains crucial information about medical images (Santos et al., 2020). At last, a "Vertex Index" is typically used to describe the indexing of vertex positions or identifiers within graph data structures. It effectively represents and manipulates complex graphic objects, like 3D modeling, graphics rendering, and graphic databases (Siadat et al., 2005).

Technologies for Data Security and Privacy

The only technology mentioned in the selected references is the removal of identifiers (Elbers et al., 2020). Having data without any identification is advantageous for generating data analysis models. However, it is not user-friendly for healthcare professionals, who are seeking to create tailored treatment plans. Therefore, alternative de-identification techniques can be employed. For example, the data tokenization substitutes sensitive data with distinct tokens or references. This approach ensures that the original data is securely stored in a separate location, while only tokens are utilized within the dataset.

Quality Attributes

Quality attributes are critical in system development because they represent the performance requirements that establish criteria for the guidance of design, implementation, and testing activities (Bass et al., 2003). System quality and its related quality attributes are domain specific (DeLone et al., 2003). This section summarizes the existing quality attributes mentioned in selected references for image database systems.

Storage Size

Storage size directly influences the capacity and scalability of the database, especially with the vast volume and complexity of big data (Marcos et al., 2007). Proper allocation of storage resources ensures the database's ability for the growing number of images to prevent the storage burden from compromising system performance or incurring excessive costs (Suapang et al., 2011; Santos et al., 2022). The crux of the matter lies in the fact that methods aimed at relieving the storage burden are not without their associated drawbacks. For instance, image compression has inaccuracy during image processing and causes information loss. Also, a mere expansion of storage capacity would lead to increased costs and a time-consuming image information retrieval process. Therefore, how to balance the data storage approach and data retrieval methods with the storage size requirements can be a future research direction.

Timeliness

Timeliness refers to the ability to minimize any possible latency, like the duration between the user initiating a query and the moment the database management system (DBMS) completes the query, during the decision support process (Marcos et al., 2007). According to selected articles, the timeliness of the image database system is primarily contingent upon storage size, which directly impacts response times, as well as the index complexity, often characterized by a notable time overhead (Siadat et al., 2005; Marcos et al., 2007).

Cost

The complexity always goes hand-in-hand with cost (Hevner et al., 2012). Some well-satisfied CDSS solutions, often commercial systems, are prohibitively expensive (Amouh et al., 2005). The cost of technologies is also a reason that prevents advanced information applications in the health domain (Knickman et al., 2015). The cost of image database systems includes initial setup and ongoing operational expenses. For example, in an integrated image database system, interconnecting and extracting image source data from multiple data sources not only incurs high setup costs due to establishing connections between different departmental servers but also results in high operational costs as data exchange is required among various servers (Cao et al., 2003). F

ull-text indexing query is also identified as a highly costly process (Marcos et al., 2007). Some studies suggest that knowledge-based segmentation can reduce certain expenses. However, such an approach requires domain experts with relevant knowledge to perform manual segmentation, leading to time-consuming and labor-intensive processes (Siadat et al., 2005). Therefore, it is essential to find a balance between the cost of human labor and technology.

Interoperability and Information Exchange

Interoperability is the ability of the system to exchange and share information between different systems (Handler, 2004). It addresses the database's capability to seamlessly integrate and exchange image data with diverse, heterogeneous sources and systems for efficient data sharing and collaboration (Santos et al., 2022). For example, storage resource broker (SRB) supports shared collections distributed across multiple organizations and heterogeneous storage systems, illustrating how interoperability is applied in managing diverse data sources (Marcos et al., 2007). In addition, DICOM has been widely recognized and utilized for enabling the efficient exchange of medical images and related information via standardizing and converting image data from various sources into a consistent format (ACR-NEMA, 2004; Cao et al., 2003; Santos et al., 2022). Furthermore, this standard also facilitates efficient and standardized communication between different medical imaging modalities

(Suapang et al., 2011).

Data Security and Privacy

Data security and privacy are important in the protection of sensitive or personal information in the database system of the health domain (Elbers et al., 2020). While data security hasn't been specifically mentioned in selected articles, some existing technologies do incorporate data security elements. For instance, DICOM considers data protection and privacy issues in addition to format standardization by removing sensitive data from DICOM headers, following a methodology akin to the safeguarding of clinical data (Santos et al., 2022). Additionally, general cloud drivers often offer data security services.

Data Validation

Data validation is a critical aspect of image databases, including the verification of accuracy, completeness, and integrity of image data within the database. Reliable image data is indispensable for research, decision-making, and preventing erroneous outcomes (Cheng et al., 2019). The implementation of robust data validation mechanisms has been approved by a DICOM application called VA-PODR, which carries out the external validation and calibration of a prognostic model for mortality among patients with non-small cell lung cancer, showcasing the significance of validated data in various medical contexts (Elbers et al., 2020).

Discussions

To the best of our knowledge, this is the first systematic literature review focusing on functionalities, technologies, and quality attributes in the implementation of image database systems in CDSS simultaneously. This SLR answers three research questions with some new findings. The three functionalities are data storage, information retrieval, and data security and privacy. The data storage can be implemented by DICOM standard as the image compression technology and vector or pixel-oriented 2D string technologies. Technologies used in information retrieval include different types of indexing and content-based image retrieval or knowledge-based segmentation as socialization and feature extraction methodologies. Data security and privacy are normally accomplished by de-identification. The SLR also summarized six quality attributes, including storage size, timeliness, cost, interoperability, data security or privacy, and data validation.

Table 4. Relationship Between Functionalities, Technologies, and Quality Attributes

Functionality	**Methodologies**	**Technologies**	**Quality Attributes**					
			Storage size	**Timeliness**	**Cost**	**Interoperability**	**Security / Privacy**	**Data validation**
Data Storage	Cloud or Local Driver		X	X	X	X	X	
	Image compression	DICOM	X			X	X	X

Functionality	Methodologies	Technologies	Quality Attributes					
			Storage size	**Timeliness**	**Cost**	**Interoperability**	**Security / Privacy**	**Data validation**
	2D string	Vector or Pixel-oriented						
Information retrieval	Query	Indexing		X	X			
	Localization + feature extraction	CBIR and Knowledge-Based Segmentation			X			
Data Security and Privacy	De-identification	Removing identifier					X	

Although multiple literature reviews summarized the functionalities and technologies used in image database systems, none of them consider their relationships with quality attributes. The summarized answers are represented in Table 4, showing the relationship between functionalities, related technologies, and quality attributes.

The table illustrates that data storage is associated with all quality attributes. Notably, the "cloud or local driver" methodology lacks specific associated technology yet exhibits the most designed quality attributes, with the exception of data validation. This peculiarity arises from the service-oriented nature of cloud-based systems and the hardware-oriented nature of local drivers. In contrast, the specialized image processing technique known as "2D string" does not align with any quality attribute. This observation may be due to the lack of relevant research rather than inherent limitations of the technology itself. Technically, the 2D string format can reduce storage requirements by representing images in a structured, mathematical, and vector-based format, rather than storing the images themselves. However, this approach is risky on information loss, which can impact data validation. Therefore, exploring the integration of 2D string and image compression may prove more advantageous for comprehensively addressing all quality attributes.

Another advantage pursued by this research endeavor is the scalability of the image database. System scalability is highly related to data storage, as it pertains to the database's capacity to accommodate growing data volumes and evolving user demands while maintaining optimal performance. It is a fundamental aspect of image database management, ensuring that the system maintains its responsiveness and efficiency during expansion. Notably, the vector-oriented structure of 2D String proves advantageous for tasks that require the scalability and adaptability of image data. Therefore, the integration of 2D String and image compression as foundational technologies for data storage represents a prospective avenue for future scientific research.

DICOM can serve as the designated standard format for such research endeavors, given its current status as the most extensively adopted format. Moreover, DICOM, as the established framework for the delineation of data structures pertaining to medical images and associated information, effectively confronts certain challenges pertaining to the exchange of information among diverse systems and tools (Marcos et al., 2007).

Furthermore, DICOM also serves as a de-identification technique. It can not only remove identification information but can also remove some other sensitive data through a process similar to the one used for clinical data (Elbers et al., 2020). This underscores the need for maintaining data security and privacy in medical imaging. With the increasing volume of big data, data security is becoming increasingly important. Enhancing the security of image database systems will inevitably become a crucial factor that database developers must consider.

References

Amouh, T., Gemo, M., Macq, B., Vanderdonckt, J., ElGariani, A. W., Reynaert, M. S., Stamatakis, L., Thys, F. (2005). Versatile Clinical Information System Design for emergency departments. IEEE Transactions on Information Technology in Biomedicine, 9(2), 174–183. https://doi.org/10.1109/titb.2005.847159

Bass, L., Klein, M., Bachmann, F. (2002). Quality attribute design primitives and the attribute driven design method. Software Product-Family Engineering, 169–186. https://doi.org/10.1007/3-540-47833-7_17

Berner, E. S. (2007). Clinical decision support systems (Vol. 233). Springer Science+ Business Media, LLC.

Bhaya, C., Obaidat, M. S., Pal, A. K., Islam, S. H. (2021). Encrypted medical image storage in DNA domain. ICC 2021 - IEEE International Conference on Communications. https://doi.org/10.1109/icc42927.2021.9500718

Cai, W., Feng, D., Fulton, R. (2000). Content-based retrieval of dynamic PET functional images. IEEE Transactions on Information Technology in Biomedicine, 4(2), 152–158. https://doi.org/10.1109/4233.845208

Cao, P., Hashiba, M., Akazawa, K., Yamakawa, T., Matsuto, T. (2003). An integrated medical image database and retrieval system using a web application server. International Journal of Medical Informatics, 71(1), 51–55. https://doi.org/10.1016/s1386-5056(03)00088-1

Chang, N. S., Fu, K. S. (1979). Query-by-pictorial-example. COMPSAC 79. Proceedings. Computer Software and The IEEE Computer Society's Third International Applications Conference, 1979. https://doi.org/10.1109/cmpsac.1979.762512

Chang, S. K., Yan, C. W., Dimitroff, D. C., Arndt, T. (1988). An intelligent image database system. IEEE Transactions on Software Engineering, 14(5), 681–688. https://doi.org/10.1109/32.6147

Cheng, D., Ramos-Cejudo, J., Tuck, D., Elbers, D., Brophy, M., Do, N., Fillmore, N. (2019). External validation of a prognostic model for mortality among patients with non–small-cell lung cancer using the Veterans Precision Oncology Data Commons. Seminars in Oncology, 46(4–5), 327–333. https://doi.org/10.1053/j.seminoncol.2019.09.006

Chock, M., Cardenas, A. F., Klinger, A. (1984). Database structure and manipulation capabilities of a Picture Database Management System (PICDMS). IEEE Transactions on Pattern Analysis and Machine Intelligence, PAMI-6(4), 484–492. https://doi.org/10.1109/tpami.1984.4767553

DeLone, H. H., McLean, R. E. (2003). The Delone and McLean Model of Information Systems Success: A ten-year update. Journal of Management Information Systems, 19(4), 9–30. https://doi.org/10.1080/07421222.2003.11045748

Elbers, D. C., Fillmore, N. R., Sung, F.-C., Ganas, S. S., Prokhorenkov, A., Meyer, C., Hall, R. B., Ajjarapu, S. J., Chen, D. C., Meng, F., Grossman, R. L., Brophy, M. T., Do, N. V. (2020). The Veterans Affairs

Precision Oncology Data Repository, a clinical, genomic, and Imaging Research Database. Patterns, 1(6), 100083. https://doi.org/10.1016/j.patter.2020.100083

Elmasri, R., Navathe, S. (2020). Fundamentals of Database Systems. Pearson.

Georgiou, A., Prgomet, M., Markewycz, A., Adams, E., Westbrook, J. I. (2011). The impact of Computerized Provider Order Entry Systems on medical-imaging services: A systematic review. Journal of the American Medical Informatics Association, 18(3), 335–340. https://doi.org/10.1136/amiajnl-2010-000043

Gordillo, N., Montseny, E., Sobrevilla, P. (2013). State of the art survey on MRI Brain Tumor Segmentation. Magnetic Resonance Imaging, 31(8), 1426–1438. https://doi.org/10.1016/j.mri.2013.05.002

Handler, J. A. (2004). Emergency medicine information technology consensus conference: Executive summary. Academic Emergency Medicine, 11(11), 1112–1113. https://doi.org/10.1197/j.aem.2004.08.005

HealthIT. (2018, April 10). Clinical decision support. HealthIT.gov. https://www.healthit.gov/topic/safety/clinical-decision-support

Hevner, A., Chatterjee, S. (2010). Design research in information systems. Integrated Series in Information Systems. https://doi.org/10.1007/978-1-4419-5653-8

Hill, D. L., Batchelor, P. G., Holden, M., Hawkes, D. J. (2001). Medical image registration. Physics in Medicine and Biology, 46(3). https://doi.org/10.1088/0031-9155/46/3/201

Kitchenham, B. (2004). Procedures for performing systematic reviews. Keele University, 33(2004), 1–26.

Knickman, J., Kovner, A. R., Jonas, S. (2015). Jonas and Kovner's health care delivery in the United States. Springer Publishing Company, LLC.

Lopez, M. H., Weingarten, S., Teich, J. M., Middleton, B., Mackay, E., Lomotan, E. A., Kawamoto, K., Josephs, M., Gandhi, T. K., Bonner, H. I., Bates, D. W., Bakken, S., Tcheng, J. E. (2023). Optimizing Strategies for Clinical Decision Support Summary of a meeting series. National Academies Press.

Marcos, E., Acuña, C. J., Vela, B., Cavero, J. M., Hernández, J. A. (2007). A database for medical image management. Computer Methods and Programs in Biomedicine, 86(3), 255–269. https://doi.org/10.1016/j.cmpb.2007.03.006

OCR, O. for C. R. (2023, February 22). Methods for de-identification of phi. HHS.gov. https://www.hhs.gov/hipaa/for-professionals/privacy/special-topics/de-identification/index.html

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The Prisma 2020 statement: An updated guideline for reporting systematic reviews. International Journal of Surgery, 88, 105906. https://doi.org/10.1016/j.ijsu.2021.105906

Santos, M., Silva, A., Rocha, N. P. (2020). DICOM metadata quality analysis for mammography radiation exposure characterization. Trends and Innovations in Information Systems and Technologies, 155–164. https://doi.org/10.1007/978-3-030-45688-7_16

Siadat, M.-R., Soltanian-Zadeh, H., Fotouhi, F., Elisevich, K. (2005). Content-based image database system for epilepsy. Computer Methods and Programs in Biomedicine, 79(3), 209–226. https://doi.org/10.1016/j.cmpb.2005.03.012

Sim, I., Gorman, P., Greenes, R. A., Haynes, R. B., Kaplan, B., Lehmann, H., Tang, P. C. (2001). Clinical Decision

Support Systems for the practice of evidence-based medicine. Journal of the American Medical Informatics Association, 8(6), 527–534. https://doi.org/10.1136/jamia.2001.0080527

Suapang, P., Yimmun, S., Puditkanawat, A. (2011). Web-based medical image archiving and communication system for teleimaging. 2011 11th International Conference on Control, Automation and Systems, 172–177.

Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N., Kroeker, K. I. (2020). An overview of clinical decision support systems: Benefits, risks, and strategies for Success. Npj Digital Medicine, 3(1). https://doi.org/10.1038/s41746-020-0221-y

Thomas, J. D. (1995). The DICOM image formatting standard: What it means for echocardiographers. Journal of the American Society of Echocardiography, 8(3), 319–327. https://doi.org/10.1016/s0894-7317(05)80042-2

Zhang, J., Xiao, W., Zhang, S., Huang, S. (2017). Device-free localization via an extreme learning machine with parameterized geometrical feature extraction. Sensors, 17(4), 879. https://doi.org/10.3390/s17040879

Zhuang, Y., Jiang, N. (2023). Progressive detail-content-based similarity retrieval over large lung CT image database based on WSLN model. Expert Systems with Applications, 228, 120209. https://doi.org/10.1016/j.eswa.2023.120209

Zloof, M. M. (1977). Query-by-example: A data base language. IBM Systems Journal, 16(4), 324–343. https://doi.org/10.1147/sj.164.0324

Author Information

Ruizhi Yu

https://orcid.org/0009-0005-7108-4592

University of Nevada Las Vegas

4505 S Maryland Pkwy, Las Vegas

NV 89154-9900

United States

Contact e-mail: *ben.yu@unlv.edu*

Yubo Fu

http://orcid.org/0000-0001-9896-8666

Colorado State University Pueblo

2200 Bonforte Blvd, Pueblo

CO 81001

United States