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Integrating Spatial Computing with Clinical Pathology for Enhanced Diagnosis and Treatment Informatics in Healthcare

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***Abstract*—This paper investigates spatial computing, which is a pathological transformational modern technology that integrates the physical and digital realms and has the potential to revolutionize pathology healthcare. Pathology as a medical specialist plays a crucial role in patient care by providing essential information for diagnosis, treatment planning, and disease monitoring. It studies and diagnoses diseases by examining tissues, organs, bodily fluids, and cells. Pathology is a broad field with three main branches: Anatomic pathology, Clinical pathology, and Molecular pathology. This study investigates the possibilities of spatial computing in radiography and clinical pathology with emphasis on diagnosis accuracy, medical education, workflow efficiency, and the outcomes in the patients. Augmented Reality (AR) medical devices guide pathologists in real-time during diagnostics procedures. The digital reproduction of tissue samples to allow pathologists to examine specimens in three dimensions is a significant utilization of spatial computing in virtual microscopy. This process allows remote collaboration between pathologists and laboratories, provides health informatics as seen in electronic health records (EHRs), improves diagnosis, and presents a platform with learning experiences in the medical field. Patients can interact with three-dimensional simulations of their anatomy, which helps them make more educated treatment decisions provided via the pathology findings and treatment alternatives in an immersive format. As this technology advances, its potential to transform pathology practice and improve patient care remains high. This review describes technological perspectives and discusses the statistical methods, clinical applications, potential obstacles, and directions of spatial computing in clinical pathology.**

***Keywords*— Telepathology informatics; augmented reality; pathology healthcare; spatial computing; diagnosis and treatment.**

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I. INTRODUCTION

Clinical pathology facilitates diagnosis and test results, and these tests are performed on fluids including blood, urine, and other bodily fluids to detect and monitor various disease-related conditions. The integration of spatial computing via augmented reality technology offers many possibilities in the fields of clinical pathology and radiography. One such is the AI-powered microscope, Augmented reality microscopy (ARM) that can make real-time inferences in the laboratory. ARM technology converts the traditional light microscope into a digital pathology platform and offers better accuracy as the measurements and stain quantifications to enhance the visualization of cellular components in simple morphometrics are reproducible. This allows pathologists to skip the step of digitizing slides and go straight into digital using the ARM smart microscope accessory. One instance of a clinical practice where automated approaches has been successfully implemented is the quantification of Immunohistochemical (IHC) staining in pathology [1]. Image analysis is a more accurate way to quantify the shape of individual cells or important tissue elements like glands. The Augmented Reality (AR) pathology applications enhance teleconsultation and telepathology and it is helpful in research and technology. This technology provides parallel viewing and enables remote pathologists and stakeholders to view histopathology slides that one microscope user sees as shown in Fig. 1.

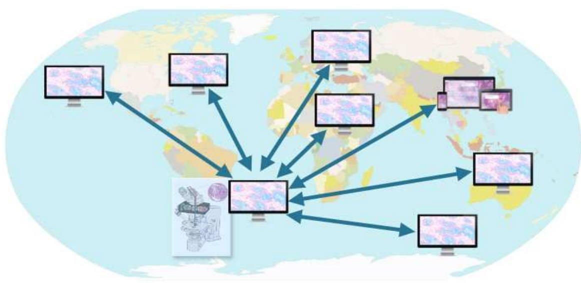

Fig. 1 Simultaneous viewing of pathology screens across various locations through Microscope integrated Telepathology

Image analysis and Artificial Intelligence (AI) algorithms enhance the view of the image in the eyepiece of the microscope. Image analysis and machine learning methodologies have been adopted to assess spatial arrangement features of the immune response within digitized autopsied H&E microscopy tissue images [2], [3] of the lungs in patients with coronavirus disease [2]. There are concerns that the AR visibility is too strong for the eye, and this can be improved upon as the technology enhances. These methodologies play a crucial role in quality control to standardize the quality of images in computational pathology [4] and also the quality assurance for whole-slide image testing. The digital information returned to the microscope by the ARM includes algorithms and AI from the developer enabling the pathologists to select which image analysis tools to use in the microscope. This technology is currently viable from technological medical equipment manufacturers like Augmentiqs and Evident (formerly Olympus) which makes the SZX-AR1 module. To improve throughput, provide guidance for the pathologists, simplify operations, and perform training via the interfaces on which the images are projected.

A. Literature Review

Spatial computing as a revolutionary approach in pathology healthcare is a transformative technology that merges physical and digital dimensions. The technologies that are essential to spatial computing are Artificial intelligence, the Internet of Things (IoT), Cloud computing, Blockchain, Extended reality (XR) encapsulating Augmented Reality (AR), Virtual Reality (VR), Mixed Reality (MR), and the interpolated technologies in between. XR is changing a variety of business sectors, including healthcare, education, and retail, as well as ordinary consumer encounters. By incorporating digital features into a live view, augmented reality (AR) augments or enhances your surroundings. This is typically achieved by utilizing a smart device.

TABLE I
XR TECHNIQUES APPLICATION IN PATHOLOGY

XR	Description	Clinical Applications
AR	Enhances the real world with an overlay of digital elements. Accessible by the user of a smartphone	• AR Surgery planning • Training • Spatial awareness • Biomedical Education • 3D Imaging • Immunohistochemistry • Predictive models • Telehealth
VR	Fully virtual, immersive simulated environment	• VR Cell Biology • VR 3D data visualization • Immersive Interaction
MR	Blend and allows the interaction between the virtual and physical worlds	• Image visualization using MR glasses. • Holographic 3D objects

Augmented reality (AR) medical devices assist pathologists to perform real-time diagnosis. Using virtual microscopy, digital reproductions of tissue samples allow a three-dimensional examination to be carried out [3]. This facilitates remote collaboration, enhances diagnosis, and supports learning experiences. Telepathology involves converting histological or macroscopic tissue images from glass slides into digital format for transmission via telecommunication pathways, facilitating diagnosis, consultation, and medical education [5]. Telepathology leverages spatial computing to access digital pathology images and diagnostic tools remotely [6], reducing delays and improving interdisciplinary interaction. Pathologists often seek second opinions from local experts, whether during rapid frozen section assessments of tumor margins intraoperatively [5] or when encountering challenging or new cases. Spatial visualization aids pathologists in understanding disease development, leading to better treatment planning and patient education. Typically, this process requires physically transporting glass slides in most settings. Overall, spatial computing applications enhance diagnosis accuracy, optimize operations, and improve patient outcomes in pathological healthcare.

The adoption of spatial computing in clinical pathology however presents itself with challenges. According to research from [7], this technology requires specialized hardware and IT infrastructure to implement spatial computing. Healthcare organizations must invest in the specified suitable infrastructure to support spatial computing. In comparison to the traditional systems, these novel computing platforms have limited application to the ecosystem which can affect global adoption. Among the challenges is ensuring that the algorithms are compliant with regulatory standards for testing and clinical application [7]. The digital pathology devices used in diagnostic reporting usually require regulatory approval [1], [6].

Numerous research groups are delving into these questions, unveiling an array of intriguing solutions. These include employing generative adverse neural networks to augment the number of rare lesion images and it requires large-scale training sets to get accuracy and significant performance [7][8]. Implementing computational staining techniques for assigning colors to histological section images and establishing consortia for generating large-scale histological image datasets. Contributions are being made from various regions worldwide, as seen in projects like the National Institutes of Health's Data Generation Projects for the NIH Bridge to Artificial Intelligence program to enable Artificial Intelligence/Machine learning methods to address key biomedical and behavioral challenges [7], [9], [10]. Whole Slide Imaging is the process through which pathologists obtain virtual slides that can be analyzed via a computer. It is a recent imaging that has to do with the scanning of conventional glass slides to produce digital slides. The special device for slide digitization is called a “Whole slide scanner”.

There is a distinction between whole slide imaging and augmented reality in pathology healthcare. The two technologies can potentially improve pathology informatics in healthcare. However, the distinction is that Augmented reality digitally enhances the interaction of the pathologist with digital pathology data, while whole slide imaging focuses on the management and digitizing of pathology slides. Spatial computing in clinical pathology represents a pivotal frontier in modern healthcare, offering profound insights into the intricate relationships between spatial patterns within tissues and disease outcomes. Recent advancements in neuroimaging techniques, as highlighted by [11], demonstrate the potential of multimodal imaging modalities like Magnetic resonance imaging (MRI) and Diffusion tensor imaging (DTI) in identifying novel structural biomarkers for traumatic brain injury prognosis. DTI is an MRI technique that measures water molecule diffusion and its directionality. Leveraging advanced processing methods and connections, these technologies unveil crucial information on brain network properties, revolutionizing outcome prediction in related cases. Similarly, the utilization of computational staining and convolutional neural networks, as discussed in [12], showcases the power of spatial analysis in deciphering tumor-infiltrating lymphocytes and their impact on overall survival in diverse cancer types. By integrating these findings, spatial computing emerges as a transformative tool in clinical pathology, paving the way for personalized treatment strategies based on spatially explicit disease features.

II. Materials and Method

In the realm of clinical pathology and radiography, there is a growing interest in the integration of spatial computing to enhance diagnostic capabilities and streamline pathological processes. Recent advancements in computational power and image analysis algorithms have enabled the development of computer-assisted analytical approaches for radiological data and digitized histopathology slides. Leveraging advancements in online prediction and estimation of dynamic spatiotemporal processes, such as those demonstrated by [13], researchers can refine parameter estimates and predictions in real-time through a robust empirical Bayes framework. By incorporating tools like Geographical Information Systems, pathologists and practitioners can enhance the expansion of the electrical network and streamline project-related processes. The innovative use of skewed-normal proposals and sequential empirical Bayes methods not only improves estimation accuracy [11][13] but also ensures the eco-friendly generation of enriched e-reports. These methodological approaches not only optimize data analysis but also enable efficient decision-making in clinical pathology settings, underscoring the critical importance of research methodology in utilizing spatial computing effectively.

A. Statistical Method of AR in Pathology

There are key statistical methods that are crucial in the application of Augmented Reality in pathology healthcare including image processing analysis, machine learning and deep learning, and clinical trials as illustrated in Fig. 2 below. These methods are essential for the development, examination, and deployment of AR technology in pathology healthcare.

1) Image Processing and Analysis: Statistical approaches are used for alignment, image segmentation, feature extraction and classification to analyze pathological images effectively. The varying algorithms of image processing and analysis based on pattern recognition, artificial intelligence, and computer graphics have been proposed to extract biomedical images [14]. Imaging applications such as radiomics–which refers to medical images and understanding various medical conditions, help to identify quantitative features in medical images. Other image applications include registration, optimization, quantification and detection.

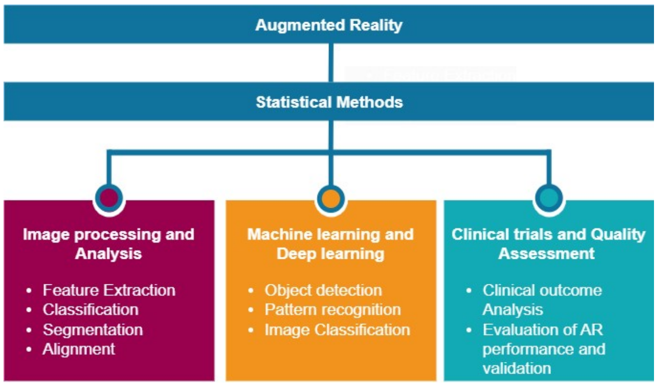

Fig. 2 AR in Pathology: Statistical Methods Utilization

2) Machine learning and deep learning: In augmented reality systems, the application of AI particularly machine learning and deep learning techniques to tasks such as image classification, object detection, and pattern recognition is performed. Research suggested fusing Edge Intelligence interfaced with several Internet of Medical Things (IoMT) enabled bio-sensors to improve the overall Quality of Service (QoS) of the system using a combination of IoMT and Machine Learning (ML) techniques [15]. Together, these sensors create a body area sensor network that logs health data. For AI/ML training applications, quality data must comprise precise, accurate and comprehensive information. A set of data points is used to build ML models, which are then trained using mathematical and statistical techniques to predict novel data [16].

3) Clinical Trials and Quality Assessment: With the influx of these technologies, safety and effectiveness are significant. Approaches applied in detecting problems include the analysis of the administrative databases used in standardized laboratory practices. Statistical methods are essential for quality assessment in the design and analysis of clinical trials utilizing AR interventions in pathological healthcare. Clinical studies are analyzed based on AR devices such as smart glasses [17]. To ensure the quality of healthcare service, statistical approaches are utilized to evaluate the precision and dependability of diagnoses based on AR in comparison to conventional methods.

B. Clinical Pathology Dataset

The amalgam of AR in the healthcare sector improves the potency and reliability of these systems. Research has provided datasets relating to pathology healthcare. Medical data is available online from repositories such as NIH, Open-access medical image repositories, clinical trial registries, and digital health record systems. These datasets have influenced AI algorithms, such as Augmented Reality, to understand the models describing the human body. Various machine learning models have been taught to identify abnormalities connected to health in human vitals. For anomaly detection, researchers looked into seven supervised classification machine-learning techniques [15]. Random Forest has achieved 95% accuracy in these trained models.

1) Virtual Pathology dataset- University of Leeds: Virtual Pathology division at the University of Leeds boasts a substantial collection of approximately ninety terabytes of digital slides, comprising around 300,000 images [18]. These resources serve as a cornerstone in supporting the department's myriad computational research endeavors (University of Leeds). Utilizing a variety of high-performance virtual machines, the division develops advanced algorithms tailored to its needs. These algorithms are subsequently deployed onto dedicated servers, complete with integrated web services for easy accessibility by researchers.

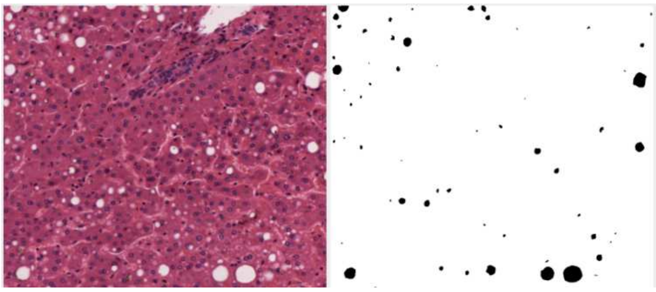

Fig. 3 Virtual slide of liver tissue (left) and segmented image (right)

The algorithm detects the fat globules which are the white in the virtual slide shown in Fig.3 above and produces a segmented image to indicate the location details of the fat globules on the right as shown in Fig.3 including the size and quantity, from the virtual slides. Its high-performance computing clusters house over three thousand processors capable of parallel processing. The Virtual Pathology Powerwall project enhances the visualization of extensive image processing results, streamlining the evaluation of algorithmic performance.

2) CheXpert: A sizable dataset, CheXpert, has 224,316 chest radiographs from 65,240 patients. This examines various methods for training convolutional neural networks to produce the probability of these observations given the frontal and lateral radiographs that are available using the uncertainty labels obtained by the labeler intended to identify the existence of the fourteen observations in radiology reports [19]. The labeler is designed to identify the existence of observations in radiology reports [19]. It was discovered that different uncertainties are helpful for different disorders based on a validation set of two hundred chest radiography scans that were manually annotated by three board-certified radiologists.

3) IEEE Data port: The IEEE data port hosts the collection of datasets [20]. Using the smartphone camera for the various microscopic fields of view, [21] from the Division of Biomedical and Health Sciences took pictures of thick blood smear slides stained with Giemsa from 150 P. falciparum-infected patients at Chittagong Medical College Hospital in Bangladesh. The attribution is to the National Library of Medicine, National Institutes of Health, Bethesda, MD, USA. Each photograph at the Mahidol-Oxford Tropical Medicine Research Unit (MORU), Bangkok, Thailand, was carefully annotated by a skilled slide reader. All of the photos and their comments were de-identified, and they were archived at the National Library of Medicine [30].

C. Integrating AR in Clinical Pathology

Clinical pathology is among a number of fields where augmented reality has multiple potential applications. A very distinct way of improving the real world with the integration of virtual computer-generated imagery is a process of tracking the image with resources such as a webcam and overlaying the computer-generated imagery on top of a live video feed into the user's display. Enhancements to augmented reality may be in the form of sound, which can be added at the user's request and has a similar seamless interactivity with the real world. Past research has shown that a great deal of focus and integration to the enhancement of learning methodologies [22], [23] through the addition of supplementary resources, which are based on the constructivist approach. This is achieved by allowing learners to interact with the information that they are learning by providing them with an environment with tools to manipulate complex information and build on their current level of knowledge [23]. This approach would guide the learner to the correct path of learning and prevent the learner from straying off topic and learning "off the task". AR technology can effectively be integrated in clinical pathology primarily but not limited to Microscopic AR and Surgical AR as shown in Fig. 4.

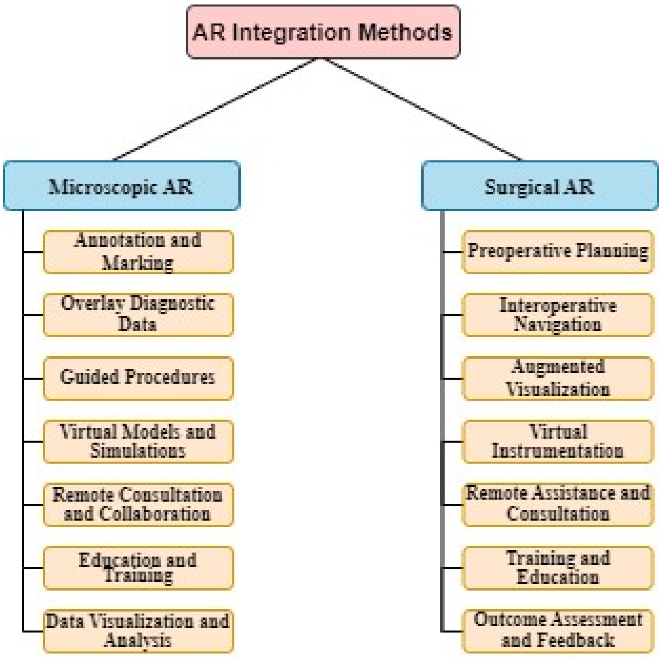

Fig. 4 AR integration methods in clinical pathology

Augmented Reality in Education and Training in Fig 4, by superimposing digital data on actual pathology specimens, AR can offer medical students, radiographers and pathologists immersive experiences. This can help practice diagnostic skills and learn pathology concepts. Pathologists need enough training and confidence in digital pathology to take advantage of it [24] and experience the drastic improvements that AR brings to the health sector. Augmented Reality Services in education and training enable users to interact with virtual and real-time applications that explain and demonstrate concepts through multimedia, computer-based simulations, animations, and statistical software. By integrating a microscope with augmented display technology and precise deep-learning algorithms [25], real-time detection and highlighting of cancerous cells become possible. This advancement facilitates the detection of breast cancer lymph node metastasis and prostate cancer as shown in Fig.5.

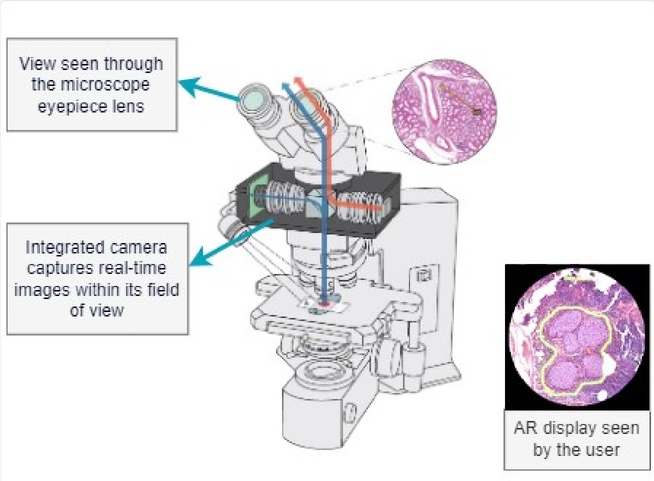

Fig. 5 AR microscope with real-time artificial intelligence integration

In Virtual Microscopy, AR technology can enrich traditional microscopy, by overlaying digital annotations, labels, or diagnostic cues on the microscopic slides. This can guide pathologists to focus on and interpret the slides more effectively. The requirement to obtain the image initially has been the largest barrier to pathology's digital transformation [24]. While scanning a glass slide takes time and expensive hardware and software, photographing slides is tedious and does not allow you to view the complete slide. Artificial intelligence (AI) and machine learning technologies in digital pathology have emerged as a result of the potential to digitize whole-slide images of tissue, which may ultimately lead to better patient care [26], [27]. In Telepathology, AR technology can enable pathologists to consult each other remotely and more effectively by sharing the live view of microscopic slides or pathology specimens, along with its live digital annotations and input. Surgical Pathology has seen the application of guiding the pathologist and surgeon during surgery, by virtually overlaying critical pathology findings that help the surgeon in real time. It can also guide the resection of tissues and tissue margins. It can also be used to provide the live histologic analysis of the resected tissue sample.

Optimization of workflow to help pathologists through hands-free access to patient data, specimen information, and protocols within the lab, AR has been found to play an important role. Pathologists can make use of AR glasses or headsets for easy retrieval of necessary data without disruptions in their work process. Through image analysis, it can identify and extract features in greater detail in comparison to the assessment of the pathologists [1][3] providing improved models beyond manual strength In Diagnostic Assistance, AR applications can help pathologists make the most accurate diagnosis with real-time diagnostic support, highlighting abnormal cells or structures within pathology images and giving suggestions for a differential diagnosis. AR technology is an area that has a vast use case, of which quality assurance is one. As an illustration, in pathology laboratories, it can be used to check if there is any discrepancy or if all procedures such as specimen processing, slide preparation, and diagnostic accuracy are followed correctly with instant feedback. A technique known as Patient Education Augmented Reality (AR) can be employed in creating interactive learning resources meant for patients. These resources enable the visualization of their pathology reports in three-dimensional images that facilitate comprehension of the diagnosis to a greater extent. Furthermore, this also increases the level of patient involvement and health knowledge.

The use of Information and Communication Technologies (ICT) in healthcare has shown many benefits to a wide range of patients and various illnesses given the diverse nature of tools contained within the ICT spectrum. Clinical care is an area of health where augmented reality is applicable and has the potential to make significant improvements to current practices [29]. Augmented reality provides a novel means for the exploration and visualization of data and/or physical objects. This is achieved using a visual display, which is a see-through head-mounted device for the enhancement of the real environment with virtual artifacts. An example would be overlaying a 3D virtual fracture on a patient's X-ray for ease of understanding and to potentially discover if the fracture can be manipulated back into place without the need for invasive surgery. This method reduces the cognitive load from having to understand and visualize a complex 2D image to the nature of the actual injury. Because of their accessibility and cost, digital extended reality digital reality technologies have been utilized in a variety of fields, from education to entertainment [29]. An alternative method would be to physically create the fracture with a mock bone and overlay the same 3D virtual fracture for comparative studies on the best method of fixing the fracture.

On the other hand, it must be noted that AR has enormous potential in clinical pathology; however, its use can be limited because of its massiveness and the difficulties faced by adoption. These include regulatory approval, interconnectivity with existing health systems, issues on privacy with health information, as well as specialist training for healthcare workers, among others. Nonetheless, ongoing advancements in AR technology and increasing demand for innovative healthcare solutions are likely to drive continued exploration and implementation of AR in clinical pathology.

D. Impulses and Code Structures

Through the impulses and the code structures, developers can demonstrate that spatial computing principles, particularly AR, can fit well with machine learning to uplift technology applications in health informatics and immerge more impact on clinical pathology healthcare.

1) Feature Extraction: Impulse: Eliminating non-informative parts from the medical images, which can be used for machine learning models to yield better performance. Permitting the 3D presentation of the content without being constrained by the traditional 2D display [29], extended reality modalities produce an immersive experience. Code Structure: To utilize the capability of Convolutional neural networks (CNNs) for feature extraction, establish the ResNet architectures that are already trained on medical image datasets. Those datasets could be, for example, as shown in Fig. 6, Musculoskeletal radiology (MURA) or CheXpert – these datasets are designed for the study of musculoskeletal radiographs and chest X-ray interpretation. MURA consists of over 40,000 images across different anatomical sites and CheXpert consists of over 200,000 chest radiographs [30] in the dataset.

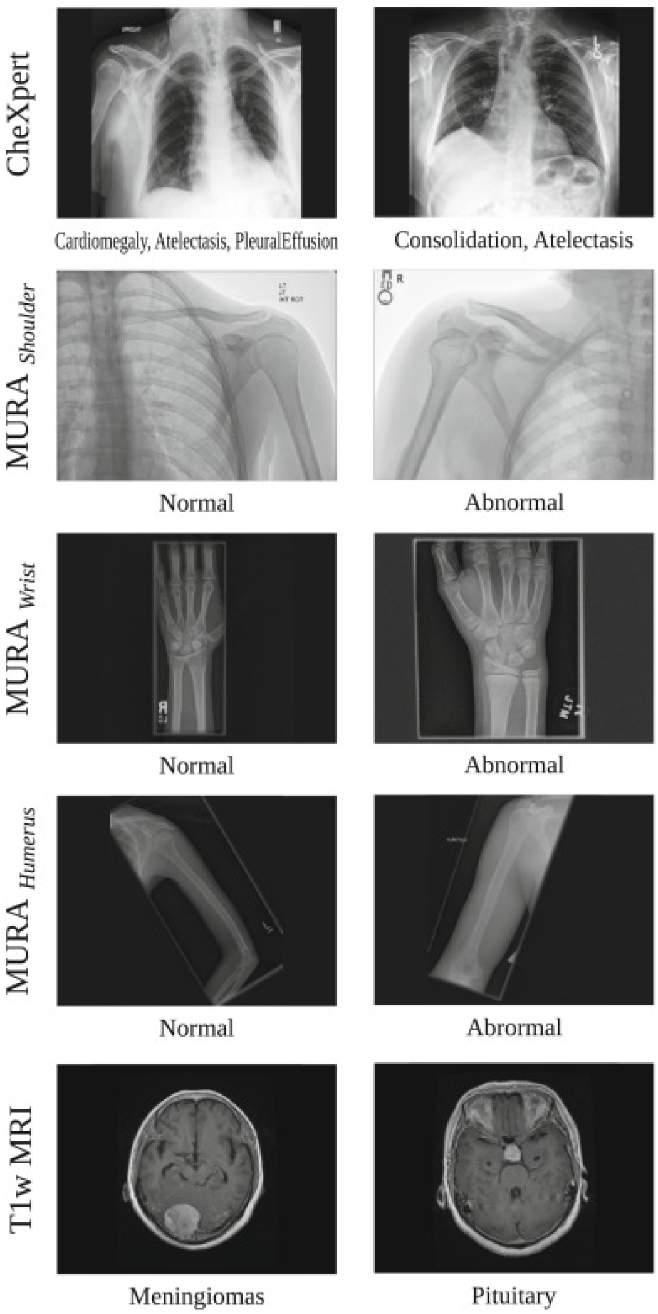

Fig. 6 Medical image classification showing representative images from the MURA and CheXpert dataset.

2) Model Training: Impulse: With machine learning, there is an enablement to distinguish between medical pictures and pinpoint the pathologies. The inertia is eliminated with ARM [24]. Code Structure: For each stage of the model development, transfer learning can be used to modify a pre-trained CNN using fine-tuning for a specific pathology dataset. Adoption of the frameworks for time-saving data training of TensorFlow.

3) Privacy and Security: Impulse: Sustain throughout the process of integrating AR pathology healthcare, the security and privacy of health data and informatics. Code Structure: Apply the practice of encryption and access control mechanisms to provide safe medical data protection. Tape into the regulatory standards, like the Health Insurance Portability and Accountability Act of 1996 (HIPAA) or General Data Protection Regulation (GDPR) in the European Union, regarding patients' confidentiality.

4) Real-time Interface: Impulse: Incorporate AI-powered augmented reality (AR) diagnostic and decision-making tools by using machine learning models with AR. Code Structure: The deployment of machine learning models in inference on mobile devices as shown in Fig.7, can be optimized through quantization and model pruning methods, respectively. Make use of updated algorithms for performing image analysis in a real-time frame.

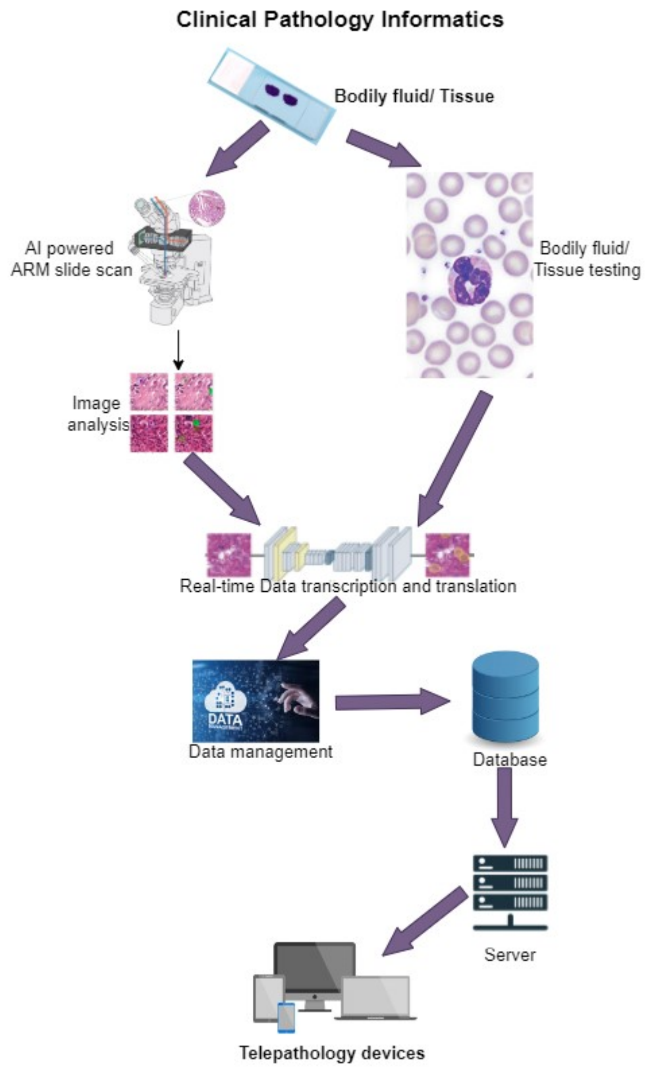

Fig. 7 Digital pathology as key in real informatics, imaging, telepathology

5) Continuous Improvement: Impulse: Continually make the machine learning models better by constantly incorporating feedback, new data and environmental changes. Code Structure: Implement tools for collecting usage data with anonymity and feedback from healthcare workers. Utilize online learning or periodic retraining to include current information and modify models due to changing environments and diseases.

6) Integration with AR Interfaces: Impulse: The development of AR interfaces to show medical display data with real-world scenarios is one of the ways by which medical students will learn and understand. Code Structure: Connect AR development kits such as AR Core (images on Android), and ARKit (images on iOS), which are machine learning inferencing libraries like TensorFlow Lite or Core ML, display diagnostic information as an overlay to the real-time video camera feed.

7) User Interaction and Feedback: Impulse: Include the user interaction and the response mechanism in the AR interface for both diagnosis and collaboration. Create an axle transporter that can move goods between different points along the production line. Code Structure: Create a user-friendly interactive interface through AR application frameworks that include hand recognition gestures alongside vocal commands. Build provisions for people to submit to and detect errors in the diagnosis for models to become continually accurate.

8) Data Preprocessing: Impulse: Prepare medical imaging data for AR visualization, medical image classification [30] and analysis. Code Structure: Use libraries like TensorFlow to preprocess medical images, remove noise, and standardize formats.

III. Results and Discussion

Clinical pathology healthcare, which screens out treatment pitfalls while enhancing accuracy in patient diagnostics, is a notable improvement in health data analysis thanks to the introduction of space computing in the medical field. Spatial computing, which includes technologies of geographical information systems (GIS), augmented reality (AR), and virtual reality (VR), lets the user see, work out, and interpret spatial data in real-time conditions. Adding spatial computing into clinical pathology ensures giving a proper diagnosis, which can be made more precise, fostering the speeding up of processes and improving efficacy, but also entails more satisfactory outcomes. Implementing spatial computing in clinical pathology will permit the doctor to examine the more complex relationships that exist within the healthcare data. Through spatial analytical approaches, clinicians can pinpoint disease domains, draw connections between clinical data findings and make more informed diagnoses that individualize therapy platforms.

A. Understanding Spatial Computing

The spatial and embodied nature of spatial computing, which intersects the physical and virtual dimensions, is the true 3D representation of the data. It is engaged without the limitations and restrictions of the standard two-dimensional displays, enriching the overall experience. Virtual reality, augmented reality and spatial computing are usually referred to as such overlapping technologies.

B. Applications in Healthcare

The usage of spatial computing extends to healthcare organizations as they aim to offer quality patient treatments and increase production effectiveness. We explore some major key applications in this section.

Medical Education in the teaching process is leveraged by the covered areas of virtual and augmented reality platforms with medical training. Realistic simulations assist healthcare professionals in training for deficiency operations for them to meet life-threatening situations. For example, a medical student can get fully engrossed in the emotional scenario of a "code blue" emergency.

Mental and Behavioral Health in virtual environments will provide mental rehabilitation and support among others. With one out of five United States (U.S.) citizens suffering from mental illness, resourceful guidance becomes pivotal. VR & AR-based technologies will help to compensate for the lack of psychiatrists or psychologists in more rural or remote areas by realizing remote interventions.

Displaying Medical Images platform where the medical images as an example Computed Tomography (CT) image, MRI results are overlaid to the patient's body shape. As motion occurs, the image adapts, making the physicians see the complete anatomy. This technology fills the gap that the focal point on laboratory testing and clinician face-to-face interaction has.

C. Obstacles and Benefits

Improved Learning in spatial computing takes the learning experience to the next level, relying on the emotions tied to the power of memory. Patient-Centric Care: Patients get better-informed choices and more customized experiences. Operational Efficiency by smoothening processes and enhanced use of resources. Security and Privacy of patient data must be of utmost importance.

Through effectively handling data formatting, network architecture and custom metrics designed to evaluate medical image analysis, these platforms open up a promising pathway for the use of spatial computing in clinical practice. Furthermore, the use of virtual microscopy and virtual slide technologies that turn out to be discovered in research will also be beneficial in supporting digital pathology transformation because this will allow for quick storage, retrieval, and analysis of images. Nonetheless, some hurdles, like initial investment reimbursement and chances of losing original identity need to be worked on firmly to ensure the success of implementation of spatial computing tools in pathological examinations, which is currently under debate as a part of the agreement on the use of virtual microscopy in routine surgical pathology for diagnostics. The measurement of challenge and consideration intends to utilize spatial computing applications to their full potential to redesign current clinical practices and speed up the diagnostic process while maintaining the level of accuracy. Spatial computing technologies like AR and VR provide immersive visualization tools that allow healthcare professionals to interact with medical data in 3D space. This immersive experience enhances understanding and interpretation of complex medical images, such as tissue samples or scans, leading to more accurate diagnoses and better-informed treatment decisions.

D. Challenges and Solutions in Spatial Computing Adoption

The adoption of spatial computing in pathology healthcare has its potential challenges, and among such challenges are data privacy [31], integration with existing pathology systems and training of clinicians.

Data privacy in healthcare is essential as pathological healthcare data contains patient's sensitive information. Spatial computing brings in data capture methods [32] which raises concerns about data privacy. Also, compliance with regulations like the Food and Drug Administration (FDA), GDPR and HIPAA is crucial [8][33]. With the methods involving collection, and transmitting patient data in different ways, compliance measures are required. To respond to these challenges in data privacy, the incorporation of robust and secure encryption techniques [33] and anonymization protocols will protect patient data during storage and data transmission. Combining blockchain decentralized mechanisms and AI techniques, including machine learning and deep learning for security and data management [31][33]. Robust access controls to ensure only authorized personnel can access the data and well-maintained audit trails for tracking the patient data access and usage facilitate accountability and compliance verification, improving data privacy.

Data standardization relating to data formats in different pathology systems can inhibit seamless integration with existing pathology systems. Spatial computing technologies compatibility issues with systems such as legacy systems [8] [33]. Legacy systems are outdated computing systems that do not allow for growth and are used by some healthcare organizations and can lead to integration challenges. Among the viable solutions, investing in tools for data transformation [31] and data mapping between different data formats and standards results in enabling healthcare system interoperability. The gap between legacy systems and spatial computing technologies can be bridged by middleware solutions. Developing Application programming interfaces that meet the standards, to aid data exchange among spatial computing integration with existing pathology healthcare systems.

Clinicians and Pathologists may lack practical knowledge of spatial computing technologies and require training to use these tools in practice. Resistance to change management in adopting new technologies and this reluctance can hinder the implementation of spatial computing applications in pathology healthcare. Resistance to change management in the adoption of new technology can inhibit the adoption of spatial computing applications in pathology healthcare. The solution to the challenges of training clinicians would be implementing training programs, which are comprehensive in nature and cover the practical and theoretical processes of functioning. Conducting feasibility studies among clinicians to provide experience and get perceived user feedback allows them to adapt to spatial computing software and incorporate these processes in the clinical workflow. Ensure that the channels of communication are open for the clinicians to discuss and allay concerns about the potential benefits of spatial computing technologies in improving patient care.

E. Practical Implementations

Following are some case studies with practical implementations of spatial computing clinical environments that encompass AR, MR, VR and Spatial Analytics.

Augmented Reality (AR) for Surgical Pathology: Case study – Recently, a study by Huang et al developed a real-time AR surgical system using AI to help surgeons when working on skin tumour surgery. This system's performance in real-world surgical practices has been validated by 106 clinical trials [34]. This technology not only delivers preoperative planning but also allows clear navigation of intraoperative samples. Also, a total of 172 patients were treated for 190 cerebrovascular lesions using intraoperative Augmented Reality [35]. The PathAI AI-driven pathology overlay solution is an AR system meant to overlay digital pathology images on the field of view of a surgeon, while he or she is undertaking an operation. This would enable a surgeon to see the real-time pathology data, such as the margins of a tumor or tissue structures, during the operation to drive more informed decisions and minimize the need for frozen section analysis. A study done at the Massachusetts General Hospital [36] has shown the feasibility and potential benefits of this AR system toward improved surgical outcomes and efficiency.

Mixed Reality for Telepathology: Case Study - Surgeons at Imperial College Healthcare National Health Service (NHS) Trust is using Microsoft's MR headset to look inside patients before they operate on them, to make procedures safer and time-efficient [37]. At the University of California, San Francisco (UCSF), pathologists were working on a telepathology project with clinicians serving remote, underserved locations to consult in real-time on complex cases. The mixed reality (MR) technology allows the pathologists at UCSF to overlay virtual annotations of live pathology images over the specimens in front of them with the HoloLens. The system enabled remote clinicians to share live pathology images and interact with virtual annotations overlaid on the specimens, facilitating precise diagnosis and treatment planning remotely.

Virtual Reality Anatomy for medical education at USCF with HTC Vive headset. The level of learners using this VR are the first-year medical students with a focus on general anatomy at the University of California, San Francisco [38].

Spatial Analytics for Cancer Diagnosis: Case Study- PathAI worked with multiple cancer centers to develop spatial analytics algorithms to examine the spatial distribution of cells in tumor tissue samples. Oral cancer and periodontal diseases are some of the diseases that affect oral health [39]. Combined with the traditional pathology data, these algorithms will point out the spatial patterns related to cancer progression and treatment response [40][41]. A retrospective study was done at Memorial Sloan Kettering Cancer Center to show the clinical use of spatial analytics in predicting patient outcomes to further enable personalized cancer treatment decisions [41][42].

IV. Conclusion

The use of spatial computing in clinical pathology healthcare is revolutionary in terms of how one utilizes technology to improve patient care and outcomes. This can be done through spatial analysis, visualization, and immersive technology that enhances the precision of data, streamlines efficiency, and boosts patient participation. Nevertheless, implementing spatial computing in clinical pathology faces a number of challenges like integrating existing data, interoperability issues, and security and privacy risks. For spatial computing to fully contribute to improving healthcare delivery and population health requires research efforts, collaboration approaches as well as innovativeness with an eye on the future. Real-time information [43] enables clinicians to make more precise diagnosis and treatment decisions [44] by leveraging advanced technologies such as artificial intelligence (AI), machine learning (ML) and virtual reality (VR). The benefits of using spatial computing in clinical pathology are valuable. It helps patients receive better results after medical laboratory checks are done, thereby reducing errors involved during diagnosis. Such errors would cause patients to undergo treatment that they do not need. Nonetheless, multidimensional interventions that comprise cooperation amongst computer scientists, physicians and policymakers would successfully facilitate the successful implementation of this innovation. By addressing issues like data confidentiality, and interoperability, among others, we can unlock the full potential of spatial computing to transform the way clinical pathology is practiced and pave the way for a new era of precision medicine. With spatial computing, the healthcare sector is undergoing a revolution. While integrating spatial computing into clinical pathology, we must overcome hurdles and embrace its potential. With technology, we can create a model that is patient-focused, efficient and innovative in the healthcare field.

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