ENHANCING PATHOLOGICAL DIAGNOSTICS: A FRAMEWORK FOR HUMAN-AI COLLABORATION FOR MULTI-USER VIRTUAL REALITY BREAST CANCER DETECTION

JUNG YUL LEE[1], KOK WAI WONG[1], MOHD FAIRUZ SHIRATUDDIN[1], SHRI RAI[1], JEREMY PARRY [2]

[1]School of Information Technology, Murdoch University, Western Australia
[2]DLS Pathology Services, Western Australia
E-MAIL: k.wong@murdoch.edu.au

Abstract:

This paper presents a framework that facilitates human-AI collaboration more effectively. The framework allows multi-users and Artificial Intelligence (AI) to collaborate in the virtual reality (VR) space. The case study presented in this paper integrates machine learning (ML) and multi-user VR technology to enhance human-ML collaboration for breast cancer diagnosis using digital pathology. ML, particularly convolutional neural networks (CNNs), has played a crucial role in breast cancer detection in recent years by automating the identification of cancerous regions in Whole Slide Images (WSIs). These results can then be visualised within a VR environment, providing pathologists with an immersive and interactive platform that supports real-time collaboration between human experts and ML. The integration of ML and VR can improve diagnostic accuracy and foster collaborative decision-making among senior and junior pathologists, potentially leading to better patient outcomes.

Keywords:

Human-AI collaboration, digital pathology, virtual reality, cancer detection

1. Introduction

AI has become a significant development area in many application domains. There has been a sharp increase in human-centred AI development in recent years especially focusing on better human interaction with the AI system [1]. An effective framework and platform are essential to facilitate human-AI collaboration in terms of interaction, user experience, XAI, and collaboration [2]. In this paper, we have chosen to feature the human-AI collaboration paradigm for breast cancer detection using digital pathology as a case study. Breast cancer is a significant health concern globally, posing a substantial threat to women's lives [3]. Timely and accurate diagnosis is crucial for effective treatment and improving patient outcomes. Traditional diagnostic methods relying on pathological analysis are often time-consuming and prone to human error, especially when handling large datasets like Whole Slide Images (WSIs). To address the growing need for more precise and rapid diagnosis, exploring new technologies that can enhance pathologists' capabilities is imperative [4].

In recent years, the field of machine learning (ML), particularly deep learning (DL), has emerged as a promising tool for automating and enhancing the accuracy of image recognition tasks, including medical diagnostics [5]. Convolutional Neural Networks (CNNs), a type of deep learning model, have shown remarkable success in identifying patterns and anomalies in medical images [6]. Studies have demonstrated the high accuracy levels that CNNs can achieve in detecting cancerous regions in WSIs, thereby supporting pathologists in making well-informed decisions [7].

The integration of VR technology in the medical field has garnered significant attention, offering immersive environments for training, simulation, and diagnostics. By combining VR with digital pathology, a novel approach emerges to enhance the diagnostic process, providing pathologists with a more intuitive and interactive platform to visualise high-resolution images. This integration has the potential to allow humans and ML to collaborate seamlessly in the virtual world to expedite diagnostic procedures and improve accuracy, ultimately leading to better patient outcomes. Furthermore, the implementation of a multi-user VR setup enables collaborative diagnostics, allowing multiple senior and junior pathologists to analyse data simultaneously with the assistance of ML, share insights, and collectively make informed decisions [8].

This paper proposes a human-AI collaboration framework that allows the strengths of ML and multi-user VR environments to improve the accuracy and efficiency of breast cancer detection. By leveraging the Camelyon16 dataset, a CNN model is trained to identify cancerous regions in WSIs, and the results are visualised within a VR environment. The VR platform not only allows pathologists to interact with the diagnostic images but also facilitates real-time collaboration among multiple pathologists, thereby enhancing the decision-making process.

2. Background

2.1. Digital Pathology

Research has shown that ML algorithms play a crucial role in developing effective predictive models for breast cancer detection and prognosis [7]. By leveraging these algorithms, researchers and physicians can enhance the accuracy of breast cancer diagnosis and prediction, ultimately aiding in early detection and treatment [9]. ML models can learn from extensive datasets of breast cancer cases and non-cancer cases to identify specific patterns and features indicative of the presence of breast cancer [10].

Models integrating ML can indeed significantly support pathologists in making more accurate and consistent diagnoses [11]. By combining digital pathology methods with advanced ML techniques, new digital cell image diagnostic features and algorithms can be developed, optimising cell classification and integrating diagnostic screening into the pathology workflow to aid in the diagnosis of various conditions, such as malignant lymphoma [11]. Further research is recommended to explore the efficiency of DL as an adjunct tool for histopathological diagnosis, potentially enhancing the accuracy of diagnosing neoplastic lesions [12]. The development of digital pathology and AI has indeed been instrumental in addressing various challenges related to pathological diagnosis and prognosis prediction [13].

2.2. Machine Learning in Pathology

ML has rapidly become an essential tool in medical imaging, with applications ranging from image segmentation to disease prediction [14]. CNNs have been pivotal in these advancements, particularly in tasks involving image classification and object detection [15]. In the context of digital pathology, CNNs have been successfully employed to identify cancerous cells in WSIs, showcasing remarkable accuracy in diagnostic tasks [16]. One notable example demonstrating the potential of CNNs in detecting breast cancer metastases is the Camelyon16 Grand Challenge, where machine-learning models surpassed human pathologists in certain diagnostic tasks, achieving higher accuracy rates in detecting small metastases that might be overlooked during manual examination [17]. These results underscore the significant impact of integrating CNNs into the diagnostic workflow to enhance the accuracy and efficiency of pathological analysis.

However, the successful application of ML in pathology is not devoid of challenges [18]. The training of CNNs necessitates large, well-annotated datasets, which can be challenging to acquire [19]. Additionally, while CNNs excel at specific tasks, variations in image quality, staining techniques, and the complexity of medical images can impede their performance [20]. Addressing these challenges requires ongoing research into model optimisation, data augmentation techniques, and the seamless integration of ML with other diagnostic tools [21]. There is also an increasing desire to incorporate human into the loop of this detection and diagnosis cycle.

2.3. Virtual Reality in Medical Applications

VR has emerged as a powerful tool in medical education, training, and diagnostics, offering immersive experiences that traditional 2D displays cannot replicate [22]. In medical education, VR simulations provide a risk-free environment for students to practice surgical procedures, interact with 3D anatomical models, and gain hands-on experience, enhancing their learning outcomes [23]. Moreover, in diagnostics, VR has the potential to revolutionise the visualisation of medical images, enabling clinicians to explore data in a three-dimensional space, potentially leading to more accurate diagnoses [22].

In the realm of digital pathology, VR presents an alternative for pathologists to examine WSIs. By immersing pathologists in a virtual environment where they can manipulate and interact with high-resolution images, VR offers a more intuitive and immersive way to analyse pathology data. This immersive experience can potentially reduce the cognitive load associated with traditional 2D image analysis, enhancing diagnostic accuracy and efficiency. Furthermore, the integration of ML results into the VR environment allows pathologists to receive real-time feedback and suggestions from the model, further aiding in the diagnostic process [24].

2.4. Multi-User Virtual Reality Environments

The collaborative potential of VR in medical diagnostics has garnered significant interest, offering multi-user environments where clinicians can share data, discuss findings, and make joint decisions [25]. In complex cases requiring input from multiple specialists sometimes, multi-user VR environments enable real-time interaction with data and each other, leading to more comprehensive analyses and better-informed decisions [25], [26], [27]. In the field of pathology, a multi-user VR environment could facilitate teams of pathologists to collaboratively analyse WSIs, leveraging the expertise and experience of each team member [28]. This collaborative approach allows pathologists to focus on different aspects of the tissue, enhancing the accuracy of diagnoses and expediting turnaround times, ultimately benefiting patient outcomes [28].

In the context of digital pathology, the utilisation of multi-user VR environments can revolutionise the way pathologists collaborate and analyse WSIs [29]. By enabling pathologists to work together in a virtual space, VR technology enhances the efficiency and accuracy of diagnostic processes, leading to more precise and timely diagnoses [30]. The integration of ML results into the VR environment further enhances the diagnostic capabilities of pathologists, providing real-time feedback and suggestions to aid in the decision-making process [31]. This collaborative approach not only improves diagnostic accuracy but also fosters a multidisciplinary approach to pathology, benefiting patient care and outcomes [32].

3. Methodology

The methodology for this research is divided into several key components: data collection, pre-processing, model building, system development, testing, and post-processing. Each step is critical in creating a robust system that integrates ML with a multi-user VR environment for the diagnosis of breast cancer using WSIs. All these are necessary to demonstrate an effective human-AI collaboration framework as proposed in this paper.

3.1. Data Collection

The primary dataset used in this study is the “Camelyon16” dataset, which is well-regarded in the field of digital pathology for its comprehensive collection of WSIs (Fig. 1) specifically aimed at the detection of lymph node metastases in breast cancer patients. The dataset provided by Radboud University Medical Centre and the University Medical Centre Utrecht, where both universities are in the Netherlands, includes 399 WSIs, with 270 designated for training and 129 for testing.

In the dataset, the Training Set has 160 normal slides (no cancer) and 110 slides containing metastases, and the Testing Set has 80 normal slides and 49 slides containing metastases. These images are provided in a high-resolution format, allowing detailed examination of tissue samples. The corresponding XML files contain annotations that highlight the regions of interest (ROIs) where cancerous cells are located, providing a crucial resource for supervised ML.

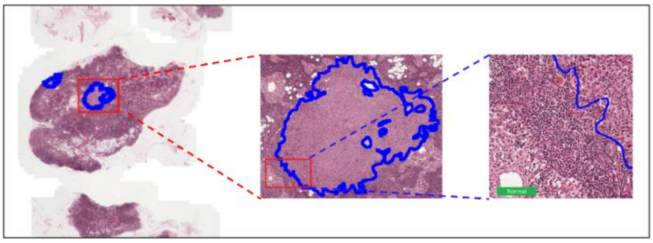

FIGURE. 1. An example of a metastatic region on the whole slide image (Bejnorji et al., 2016).

3.2. Pre-Processing

Pre-processing plays a vital role in preparing WSIs for ML by reducing their size while preserving essential diagnostic details. Given the large scale of WSIs, efficiently identifying and segmenting key areas is necessary to make data manageable. The process begins with ROI detection, where WSIs are converted from the RGB colour space to HSV to better distinguish colour information from luminance. A binary mask is then created to isolate tissue areas while eliminating the background. To refine the mask, morphological operations such as closing and opening are applied, followed by contour detection to accurately define the boundaries of the ROI.

Once the ROIs are identified, they are divided into smaller 256x256 pixel patches for further analysis. These patches are categorised as either positive (containing cancerous cells) or negative (containing normal tissue). Extracting patches from both cancerous and non-cancerous areas ensures a balanced dataset, preventing bias in ML models. By systematically segmenting the WSIs, this approach enhances the efficiency of data processing while maintaining the integrity of diagnostic information.

3.3. Model Building

This study focuses on training a CNN to classify extracted patches as either cancerous or non-cancerous with high accuracy. Given the complexity and large size of WSIs, the pre-trained GoogLeNet architecture is chosen due to its strong performance in image classification tasks, including the Camelyon16 competition. Its deep structure and efficient design make it well-suited for handling the intricate features of medical imaging data.

In addressing the challenge of a limited training dataset, transfer learning is applied. A pre-trained GoogLeNet model, which has already learned to recognise essential image features, is fine-tuned using the Camelyon16 dataset. This method speeds up the training process while improving accuracy by leveraging prior knowledge. Additionally, the final layers of GoogLeNet are modified to suit this specific classification task. The fully connected layer is adjusted to output two classes, positive (cancerous) and negative (non-cancerous), while the SoftMax layer is adapted to align with the binary classification requirement.

Due to computational constraints, only a subset of the extracted patches is used for training. However, careful management of the training process ensures the model learns to distinguish between cancerous and non-cancerous tissue effectively. In enhancing robustness and generalisability, data augmentation techniques such as rotation, flipping, and scaling are applied. These augmentations help prevent overfitting and allow the model to perform well when analysing diverse histopathological images.

3.4. System Development

A major innovation in this study is the integration of the trained CNN model into a multi-user VR environment. This system is developed using Python, MATLAB, and Unity, with each platform contributing to different aspects of the architecture. The VR setup enables real-time interaction with WSIs, allowing multiple users to engage with diagnostic data collaboratively. The overall system architecture (Fig. 2) is designed to ensure seamless integration between the computational backend and the VR interface, facilitating efficient data visualisation and interaction.

The hardware configuration consists of three primary components. A virtual machine is responsible for pre-processing, model training, and testing, featuring an Intel Xeon GPU, 32GB RAM, and Windows Server 2019 OS. It runs essential ML tools, including Python 3.6.12 and MATLAB R2020b, to process large datasets effectively. A laptop functions as the Unity server, managing the VR environment and handling communication with the trained model. The Oculus Quest serves as the client device, enabling users to access the VR environment and interact with WSIs. The system is structured to support simultaneous multi-user access, where the Unity server hosts the VR interface. At the same time, the virtual machine executes backend processes, such as running the trained CNN model and generating heatmaps based on user queries.

The VR environment, developed in Unity, incorporates custom plugins to enable real-time interaction with pathology data. It consists of two primary display planes—one showing the original WSI and another displaying the heatmap generated by the CNN model. Users can switch between different slides and heatmaps using simple controls, with the added functionality of voice communication and annotation tools to facilitate collaboration. The Oculus Quest devices connect to the Unity server, allowing users to visualise and manipulate diagnostic data in real-time, further enhancing the interactive experience.

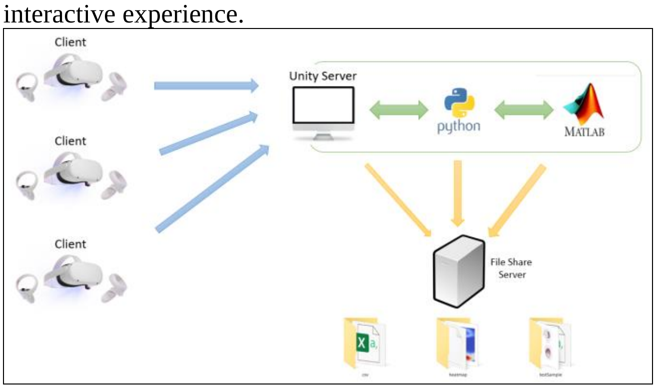

FIGURE 2. The system architecture.

3.5. Testing and Post Processing

Evaluating the CNN model within the VR environment is essential to assess its performance and usability. The testing phase involves applying the model to new, unseen WSIs and visualising the results in real-time within the VR space. This process ensures that the system can accurately classify tissue samples and provide clear diagnostic insights to users.

Testing begins with patch extraction, following the same methodology as the training phase. Patches are taken from the test WSIs while preserving their location information, including row and column indices, to facilitate precise heatmap generation. The extracted patches are then processed by the trained CNN model, which predicts the likelihood of each patch containing cancerous cells. The results are stored in a probability matrix, recording both the location and confidence level of each prediction. Post-processing focuses on generating heatmaps from the probability matrix, providing a visual representation of the model's predictions. In these heatmaps, regions with a high probability of cancer are highlighted in red, while areas with a low probability appear in blue. In enhancing clarity and reducing noise, Gaussian filtering is applied, smoothing the heatmaps for improved visualisation. This refined output allows users to interpret diagnostic data more effectively within the immersive VR environment.

3.6. Multi-User Interaction in VR

One of the primary objectives of this study is to enable human-AI collaborative diagnostics in a VR environment. The system allows multiple users to enter the same virtual space, view the same WSIs and heatmaps, and communicate in real time (Fig. 3).

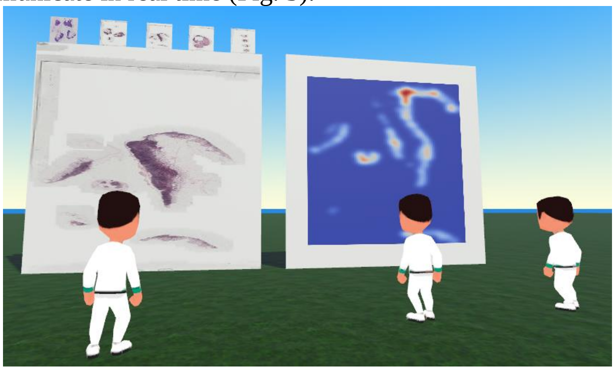

FIGURE. 3. The multi-user VR environment.

4. Results

The results of this study focus on the performance of the CNN model in identifying cancerous regions in Whole Slide Images (WSIs), as well as the effectiveness of the multi-user Virtual Reality (VR) environment in facilitating collaborative diagnostics.

4.1. Machine Learning Performance

The CNN model, built on the GoogLeNet architecture, was trained using a subset of the Camelyon16 dataset due to computational limitations. Despite the restricted training data, the model demonstrated strong classification performance on WSIs, effectively distinguishing between cancerous and non-cancerous patches.

The model achieved approximately 85% accuracy on the validation set, with a steadily decreasing cross-entropy loss throughout training. These results indicate that the model successfully learned the distinctions between malignant and normal tissue. A confusion matrix was used to further assess classification performance, revealing a relatively low false-negative rate, critical in medical applications where missing a cancerous region could have severe consequences. While the false-positive rate was slightly higher, this suggests a conservative approach, prioritising caution in predictions.

To visually interpret the model's predictions, heatmaps were generated and overlaid on the original WSIs. These heatmaps effectively highlighted cancerous regions, with red indicating a high probability of malignancy and blue representing a low probability. Gaussian filtering was applied to smooth the heatmaps, reducing noise and improving clarity, making it easier for pathologists to analyse and interpret the results.

4.2. VR Environment Implementation

The integration of the CNN model's output into the VR environment was a key component of this study, providing pathologists with an immersive and interactive 3D space to analyse WSIs and heatmaps more effectively. By incorporating VR technology, the platform enhanced data visualisation and user interaction, allowing for a more intuitive diagnostic experience.

The VR environment was designed with a user-friendly interface featuring two primary display planes: one showing the original WSI and the other presenting the corresponding heatmap. Users could seamlessly switch between different slides and heatmaps using keyboard inputs, while basic navigation and interaction tools enabled efficient exploration of the data. A major advantage of the platform was its multi-user collaboration feature, allowing multiple users to engage in the same virtual space simultaneously. Real-time interactions, such as pointing to specific slide areas or highlighting key regions, were supported, and voice communication was facilitated through the Oculus Quest's built-in microphone and speakers, enabling discussions and collaborative decision-making.

Usability feedback from pathologists who evaluated the VR system was largely positive. Many appreciated the immersive nature of the environment, which allowed for a more intuitive examination of WSIs compared to traditional 2D methods. The ability to collaborate in real-time with colleagues was also highlighted as a significant benefit. However, some users suggested that VR controls could be further refined, particularly for those less experienced with VR technology, to improve overall ease of use and accessibility.

5. Discussions

The discussion section provides a critical analysis of the results, addressing the strengths and limitations of the study and exploring potential avenues for future research.

5.1. Analysis of Results

The integration of ML and VR in this study marks a significant advancement in human-AI collaboration in digital pathology. The CNN model demonstrated good performance in identifying cancerous regions within WSIs, while heatmap visualisations provided a clear and intuitive method for interpreting its predictions. By incorporating VR, pathologists were able to interact with diagnostic data in an immersive and collaborative setting, enhancing both individual analysis and teamwork. This interactive approach has the potential to improve diagnostic accuracy and decision-making by providing an effective platform for human junior and senior pathologists to work with AI results. However, user feedback suggested that refining the VR interface could further enhance the overall experience, making it more intuitive and accessible for all users.

6. Conclusions

This study has presented an effective human-AI collaboration platform by demonstrating the potential of integrating ML and VR technologies for breast cancer diagnosis using digital pathology. The development and implementation of a multi-user VR environment, combined with a CNN model trained on WSIs, represent a viable step forward in the field of digital pathology utilising concepts in human-AI collaboration development.

This interactive system provided an intuitive way to visualise diagnostic data while facilitating real-time collaboration among medical professionals. The ability to share insights and annotate slides collectively demonstrated the potential for improved diagnostic accuracy through teamwork between multiple human pathologists and AI.

References

[1] W. Xu, M.J. Dainoff, L. Ge, and Z. Gao, “Transitioning to human interaction with AI systems: New challenges and opportunities for HCI professionals to enable human-centered AI,” Internatiola Journal Human-Computer Interaction, 39 (3), 494–518 2023.

[2] M. Raees, I. Meijerink, I. Lykourentzou, V.K. Khan, and K. Papangelis, “ From explainable to interactive AI: A literature review on current trends in human-AI interaction,” International Jourmal Human-Computer Studies, 189, 103301, 2024.

[3] A. Malik, “Application of machine learning models and parameters for prediction of breast cancer,” Pakistan Journal of Science, 75(04), 710-717, 2023.

[4] V. Rawat, K. Gulati, U. Kaur, J. Seth, V. Solanki, A. Venkatesh, D. P. Singh, N. Singh, and M. Loganathan, “A supervised learning identification system for prognosis of breast cancer. Mathematical Problems in Engineering,” 1-8, 2022.

[5] M. Awan, “Comparative analysis of machine learning models for breast cancer prediction and diagnosis: a dual-dataset approach,” Indonesian Journal of Electrical Engineering and Computer Science, 34(3), 2032, 2024.

[6] C. Dai, “ Study on breast cancer image detection and classification based on residual connected convolutional neural network (CNN),” Theoretical and Natural Science, 33(1), 231-237, 2024.

[7] S. Chen, “Breast cancer prediction based on RF-SVM,” Applied and Computational Engineering, 8(1), 657-666, 2023.

[8] M. Xie, K. Zhou, N. Patro, T. Chan, M. Levin, M. Gupta, and J. Archibald, J., “Virtual reality for vestibular rehabilitation: a systematic review,” Otology & Neurotology, 42(7), 967-977, 2021.

[9] B. Herawati, B. “Smote variants and random forest method: a comprehensive approach to breast cancer classification,” International Journal of Engineering Continuity, 3(1), 12-23, 2024

[10] O. Egwom, M. Hassan, J. Tanimu, M. Hamada, and O. Ogar, “An lDA–SVM machine learning model for breast cancer classification,” Biomedinformatics, 2(3), 345-358, 2022.

[11] G. Tang, X. Fu, Z. Wang, M. Chen, “A machine learning tool using digital microscopy (Morphogo) for the identification of abnormal lymphocytes in the bone marrow,” Acta Cytologica, 65(4), 354-357, 2021.

[12] S. Bukhari, “The efficiency of deep learning for the diagnosis of psammomatous meningioma,” The Annals of Clinical and Analytical Medicine, 12(02), 153-156, 2021.

[13] S. Matsubara, A. Saito, N. Tokuyama, N., R. Muraoka, T. Hashimoto, N. Satake, T. Nagao, M. Kuroda, and Y. Ohno, “Recurrence prediction in clear cell renal cell carcinoma using machine learning of quantitative nuclear features,” Scientific Reports, 13(1), 2023.

[14] M. Jiang, S. Lei, J. Zhang, L. Hou, M. Zhang, and Y. Luo, “Multimodal imaging of target detection algorithm under artificial intelligence in the diagnosis of early breast cancer,” Journal of Healthcare Engineering, 1-10, 2022.

[15] A. Hayat, “Breast cancer detection system from thermal images using swin transformer,” CJACSIT, 1-11, 2023.
[16] A. Sumitha, “Transfer learning-based CNN model for the classification of breast cancer from histopathological images,” International Journal of Advanced Computer Science and Applications, 15(4), 2024.
[17] M. Jubeen, A. Rahman, S. Wahid, A. Imran, A. Yasin, and I. Ihsan, “An automatic breast cancer diagnostic system based on mammographic images using Convolutional Neural Network classifier,” Journal of Computing & Biomedical Informatics, 4(01), 2022.
[18] R.M. Hamis, and R. Bhalalusesa, “AI-driven mobile application for breast cancer detection using CNN for MRI images in Tanzania,” International Journal of Computer Applications Technology and Research, 12(12), 11 - 16, 2023.
[19] J. Ruan, Z. Zhu, C. Wu, G. Ye, J. Zhou, and J. Yue, “A fast and effective detection framework for whole-slide histopathology image analysis,” Plos One, 16(5), e0251521, 2021.
[20] D. Wong, Z. Gandomkar, W. Wu, G. Zhang, W. Gao, X. He, Y. Wang, W. Reed, “Artificial intelligence and convolution neural networks assessing mammographic images: a narrative literature review,” Journal of Medical Radiation Sciences, 67(2), 134-142, 2020.
[21] S. Sunardi, A. Yudhana, and A. WindraPutri, “Mass classification of breast cancer using CNN and faster R-CNN model comparison,” Kinetik Game Technology Information System Computer Network Computing Electronics and Control 2022.
[22] S. Yadav, “Transformative frontiers: a comprehensive review of emerging technologies in modern healthcare,” Cureus, 2024.
[23] M. Sattar, S. Palaniappan, A. Lokman, A. Hassan, N. Shah, Z. Riaz, “Effects of virtual reality training on medical students’ learning motivation and competency,” Pakistan Journal of Medical Sciences, 35(3), 2019.
[24] B. Hameed, S. Somani, E. Keller, R. Balamanigandan, S. Mahapatra, A. Pietropaolo, Ş. Tonyali, P. Juliebø-Jones, N. Naik, D. Mishra, S. Kumar, P. Chlosta, and B. Somani, “Application of Virtual Reality, Augmented Reality, and Mixed Reality in Endourology and Urolithiasis: an update by YAU Endourology and Urolithiasis Working group,” Frontiers in Surgery, Vol. 9, 2022.
[25] M. Bejani, A. Taghizadieh, T. Samad-Soltani, A. Asadzadeh, and P. Rezaei-Hachesu, “The effects of virtual reality-based bronchoscopy simulator on learning outcomes of medical trainees: a systematic review,” Health Science Reports, 6(7), 2023.
[26] A. Hajnal, and M.F. Shiratuddin, (2010), “A Pilot Study on Design Performance in a Collaborative Virtual Environment,” The International Journal of Learning: Annual Review, 17(3), 509-522, 2010.
[27] M.F. Shiratuddin, W. Thabet, “A framework for a collaborative design review system utilising the Unreal Tournament (UT) game development tool,” In Proceedings of the 20th CIB W78 Conference on Information Technology in Construction. Waiheke Island, Auckland, New Zealand, April 2003.
[28] B. Ineichen, C. Cananau, M. Plattén, R. Ouellette, T. Moridi, K. Frauenknecht, S.V. Okar, Z. Kulcsar, I. Kockum, F. Piehl, D.S. Reich, and T. Granberg, “Dilated virchow-robin spaces are a marker for arterial disease in multiple sclerosis,” Ebiomedicine, 92, 104631, 2023.
[29] F. Öhman, J. Hassenstab, D. Berron, M. Schöll, and K. Papp, “Current advances in digital cognitive assessment for preclinical Alzheimer’s disease,” Alzheimer S & Dementia Diagnosis Assessment & Disease Monitoring, 13(1), 2021.
[30] B. Gilliam, L. Douglas, G. Fleisig, K. Aune, K. Mason, J. Dugas, E.L. Cain Jr, R. Ostrander, and J. Andrews, “Return to play and outcomes in baseball players after superior labral anterior-posterior repairs,” The American Journal of Sports Medicine, 46(1), 109-115, 2017.
[31] P. Parikh, B. Shah, B. Trivedi, V. Patel, S. Desai, S. Nimbalkar, and A. Phatak, “A comparison of the pulmonary valve, main pulmonary artery, and branch pulmonary artery measurements by echocardiography and computed tomography scan,” Cureus, 2021.
[32] V. Serchi, A. Peruzzi, A. Cereatti, U. Croce, “Use of a remote eye-tracker for the analysis of gaze during treadmill walking and visual stimuli exposition,” Biomed Research International, 1-6, 2016.