Chatbot Integrated Holographic System for Digital Agriculture and Education

Kübra Kara
Instituto de Investigación para la Gestión Integrada de Zonas Costeras (IGIC)
Universitat Politecnica de Valencia, Valencia, Spain
Email: kkubra@doctor.upv.es

Daniel Matheus Brandão Lent
Electrical Engineering Department
State University of Londrina, Londrina, Brazil
Email: matheus.daniel@uel.br

Alberto Ivars-Palomares
Instituto de Investigación para la Gestión Integrada de Zonas Costeras (IGIC)
Universitat Politecnica de Valencia, Valencia, Spain
Email: aivapal@epsg.upv.es

Jaime Lloret
Instituto de Investigación para la Gestión Integrada de Zonas Costeras (IGIC)
Universitat Politecnica de Valencia, Valencia, Spain
Email: jlloret@dcom.upv.es

***Abstract*— The digitalization of agriculture, known as Agriculture 4.0, is revolutionizing the way agricultural products are produced, managed, and marketed. This transformation is driven by the integration of advanced technologies, such as the Internet of Things (IoT), Artificial Intelligence (AI), big data, and digital twins. Digital twins, virtual replicas of physical systems, enable farmers to simulate and optimize agricultural operations in real-time, enhancing their decision-making process. AI plays a crucial role in analyzing vast amounts of data collected from wireless sensor networks, allowing for precision agriculture and addressing global challenges, such as food security and climate change. The adoption of digital technologies also facilitates traceability and transparency in the agricultural supply chain, ensuring food safety and quality. Among the emerging technologies, holography stands out as a promising tool for intelligent agriculture. Digital holography techniques, such as computational holography, iterative holography, Fourier-based holography, Computer-Generated Holography (CGH), Deep Holography (DH), and tensor holography, offer immersive and realistic experiences for users. The integration of holography with AI and other technologies has the potential to revolutionize digital agriculture by providing real-time monitoring, management, and interaction with crops. However, the development and implementation of these technologies must be inclusive, sustainable, and focused on enhancing the quality of life for all individuals. This study presents a communication algorithm flowchart and a system proposal to elucidate the interaction between a user and a holographic system, demonstrating the potential of holography not only in digital agriculture but also in effective human learning and communication.**

Keywords-Agriculture 4.0; Internet of Things (IoT); Artificial Intelligence (AI); Digital twins; Holography; Large Language Models (LLM).

I. INTRODUCTION

The digitalization of agriculture, also known as Agriculture 4.0, revolutionizes how agricultural products are produced, managed, and marketed. This transformation is based on the integration of advanced technologies, such as the Internet of Things (IoT), Artificial Intelligence (AI), big data, and digital twins to improve the efficiency, sustainability, and profitability of the agricultural sector [1].

Digital twins, virtual replicas of physical systems, are instrumental in agriculture. They enable farmers to simulate and optimize agricultural operations in real-time, a feature that significantly enhances their decision-making process [2]. These digital replicas collect data from Wireless Sensors Networks (WSN) distributed in fields and agricultural machinery, providing detailed information on soil conditions, weather, plant growth, and crop health [3]. By analyzing these data, farmers can make informed decisions about irrigation, fertilization, and pest control, resulting in more efficient resource use and higher productivity [4].

AI plays a crucial role in analyzing these vast amounts of data. Machine learning algorithms can predict crop yields based on historical data, optimize planting schedules, and even detect early signs of diseases or pest infestations in crops [5]. These AI-driven ideas allow precision agriculture, where water, fertilizers, and pesticides are used more effectively, reducing costs and minimizing environmental impact; this is accomplished thanks to the different technologies used, such as sensors, Global Positioning System (GPS) or the Internet of Things application (IoT) [6].

The adoption of digital technologies in agriculture not only improves crop management but also has the potential to address global challenges, such as food security and climate change [7]. This potential is underscored by a report from the United Nations Food and Agriculture Organization (FAO), which predicts a 70% increase in global food demand by 2050 [8]. Integrating technologies like artificial intelligence and big data in agriculture can help predict crop yields, optimize fertilizer and pesticide use and reduce food waste, contributing to a more sustainable future [9].

Moreover, digitalization facilitates traceability and transparency in the agricultural supply chain, ensuring the safety and quality of food that will guarantee consumer confidence [10]. Modern consumers demand detailed information about the food's origin and quality. Through blockchain and other distributed ledger technologies, it is possible to track every stage of a product's lifecycle, from

ISBN: 978-1-68558-324-8

farm to table, ensuring the authenticity and quality of the final product [11].

The use of drones and IoT sensors in agriculture has also enabled more precise and real-time monitoring of fields, contributing to more effective management and reduced operational costs [12]. This technology provides farmers with critical data that can be used to improve planning and decision-making, thereby increasing productivity and reducing environmental impact, as in the case of water, where more than half of water consumption is attributed to crop irrigation. The improvement of the irrigation system will be essential to reduce consumption; this can be achieved thanks to different monitoring technologies, in this case, the monitoring of evapotranspiration [13].

AI, a key player in the digitalization of agriculture, also aids in automating repetitive tasks, such as weeding, harvesting, and sorting of produce. This practical application of AI saves time and ensures high precision and efficiency in these tasks, freeing human labor for more complex decision-making processes [14].

The digitalization of agriculture represents a significant opportunity to transform the agricultural sector, enhancing efficiency, sustainability, and resilience to global challenges. Integrating advanced technologies, such as digital twins and AI, promises to optimize farming operations and prepare them for a more sustainable and technologically advanced future [15].

One of these digital technologies could also be holograms. Holography is an application of optical physics, specifically the science of interference and diffraction of light and waves. It enables the creation of three-dimensional (3D) images, which, in contrast to two-dimensional (2D) images, provide enhanced detail and information due to the depth and relief characteristics of holograms. Furthermore, holography is a technology applicable to diverse fields and sectors, rendering it a multidisciplinary concept. These applications encompass medicine, engineering [16], and agriculture [17]. As with other technologies, this multidisciplinary concept has evolved into digital holography, advancing classical holography to a more sophisticated level. Digital holography possesses the capability to integrate real and virtual aspects of the world through its 3D resolution, positioning this technology within mixed reality systems. This technology can significantly enhance user engagement due to low latency, as users can interact vividly with holograms through immersion without the need of special glasses, thereby stimulating multiple human senses simultaneously through haptics, smell and taste. This type of multi-sensory technology is called mulsemedia. Moreover, an additional advantage of augmented reality technology, such as holography is its capacity for integration with multiple other technologies, a concept commonly referred to as multimodal technology or interface [18].

This research is organized as follows: Section I provides an introduction of Agriculture 4.0, emphasizing the transformation and digitalization of traditional agriculture with means of digital technologies, such as IoT, AI and specifically holography. In Section II, the related work regarding intelligent agriculture and farming, LLM, various types of digital holography are discussed. The chatbot-integrated holographic system applied to digital agriculture is being proposed in Section III along with the system's architecture and communication algorithm. Section IV presents the simulation results and evaluates the performance of different language models. Finally, Section V concludes the paper with a summary of the findings, implications of AI and holography in digital agriculture and suggestions for future research directions.

II. RELATED WORK

In recent years, the integration of advanced technologies into agriculture has gained significant attention. A noteworthy contribution is the intelligent agriculture system developed by Xu et al. [17]. This innovative system employs holograms to provide real-time monitoring and management of crops. By projecting holographic data related to crop growth, soil conditions, and irrigation needs, farmers are empowered to make informed decisions without the necessity of being physically present in the field. This advancement not only enhances agricultural management efficiency but also significantly reduces water resource consumption. Looking ahead, future developments in the field of intelligent agriculture could include the integration of AI for predictive analysis and the use of drones for remote monitoring. Such advancements exemplify the potential of technology to transform traditional agricultural practices into more sustainable and efficient methods, showcasing a promising future for the industry.

The importance of accessibility in digital environments is further emphasized in research by Alabi et al. [19], which focuses on visually impaired users. Their study highlights the critical role of assistive technologies, including screen readers and adaptive user interfaces, in facilitating access to information. Implementing these technologies shows that improving digital accessibility can lead to greater participation by all users, particularly those with disabilities. His research findings underscore the need for inclusive design on digital platforms and the responsibility of developers to ensure that the needs of various user groups are considered. By prioritizing accessibility, developers can create more equitable digital environments. It is intended to use this type of technology in libraries to avoid discrimination in these environments.

The development of tools aimed at improving communication for individuals with speech disabilities has also seen significant advancements. [20] Janai et al. introduced a sophisticated text-to-speech and speech-to-text conversion tool that leverages advanced natural language processing algorithms. This tool provides rapid and accurate conversion between text and voice, facilitating smoother user interactions. Its implementation across various applications has positively impacted the daily lives of those relying on such technologies, highlighting the importance of innovation in communication aids. By enhancing accessibility, these tools empower individuals with speech disabilities, fostering more significant inclusion in society.

Another significant area of development is in the realm of Large Language Models (LLM), as presented by Brown et al. [21]. Their work on models like GPT-3 represents a groundbreaking shift in how machines comprehend and generate human language. With their transformative potential, these models utilize vast datasets and sophisticated deep learning algorithms to produce coherent and contextually relevant text, which has transformed numerous applications, from content generation to academic research assistance. The capabilities of large language models extend far beyond mere Natural Language Processing (NLP); they also facilitate human-computer interaction, making technology more intuitive and user-friendly. This technological leap has opened avenues for new research, creativity, and productivity across various fields.

As previously noted by Xu et al. [17], the utilization of digital holography can be a significant asset in agriculture. The digitalization of classical holography has given rise to various holographic techniques [22]. Computational holography employs computers to generate holograms. This technique offers the advantage of adapting and manipulating holographic projections through computational parameters; however, considering the substantial data requirements of holographic projections, high bandwidth is necessary, which can be addressed through the use of algorithms and Deep Neural Networks (DNN) [23].

Iterative holography also utilizes specific algorithms, such as the Gerchberg-Saxton algorithm. As the name suggests, iterative holography continuously refines projections to reconstruct a holographic image, phase object, eliminate twin images (although beneficial in agriculture [24]), and overcome physical barriers and obstacles of the real world [25]. While this technique may result in poor image quality methods, such as the Constrained Complex Total Variation (CCTV) regularizer exist [26] to preserve image resolution.

Another method of creating holograms digitally without the use of lenses is Fourier-based holography [27], in which a reference wave enables the retrieval of phase information about any type of wave, such as light, electron, and X-ray, scattered by an obstacle, simply by using Fourier Transform to reconstruct images.

The method shown in [28] is applicable to various disciplines and provides the capability to generate Computer-Generated Holography (CGH), which leads to the next type of digital holography. The CGH method can work with incoherent light and generating high-quality holograms through the use of algorithms. Its flexibility and versatility make it suitable for Virtual Reality (VR) and Augmented Reality (AR) [29].

Next, there is Deep Holography (DH), which also utilizes DNN to execute phase aberration corrections. Additionally, DH not only gives rise to other types of digital holography, such as tensor holography, but it also addresses one of the major challenges in holograms, which is the elimination of twin images [30]. Considering the importance and relevance of twin images in agriculture, holography may be a suitable technology in digital agriculture.

Finally, very similar to CGH is tensor holography, which is the most realistic form of digital holography. Tensor holography employs DNN and Machine Learning (ML) and can also be referred to as a physics-informed DNN technique. This technique has the capacity to project real 3D volumetric images in air, making it not only the most computationally intensive digital holography technique but also the most intricate. Scholars argue that tensor holography requires 4000 pairs of RGB-depth images for training and provides the full potential of holographic video communication, thus enabling maximum user engagement and satisfaction [30][31]. Tensor holography is the type of holography that is desired to achieve revolutionizing digital agriculture. As discussed by Huang et al. [32], holography provides 6 Degrees of Freedom (DoF), involving an immersive and realistic experience in 3D movement and rotation, physically allowing users to engage with holographic projections. This again supports the relevance of holograms in digital agriculture.

While the advancements across these domains—intelligent agriculture, digital accessibility, communication tools, and language models—demonstrate the profound impact of technology on society, it's important to note that they also come with potential risks and challenges. For instance, large language models can potentially perpetuate biases in the training data, leading to unintended consequences. As we continue to innovate, it is crucial to ensure that these technologies are inclusive, sustainable, and enhance the quality of life for all individuals. Embracing a collaborative approach in developing solutions can pave the way for a more equitable and accessible future.

III. PROPOSED SYSTEM FRAMEWORK

Large language models have proven to be a great advancement for artificial intelligence, and natural language processing. Numerous tools, such as ChatGPT, Gemini and Microsoft Copilot are already available for aiding users with faster research by interpreting multiple sources of information and answering questions. Other tools are already being studied to help health professionals to study for clinical education, practice, vascular research and scientific writing [33]. This study proposes a system to make information about different kinds of trees more accessible for people, especially biology students. It is composed of holograms, each of a different species of tree, that are connected to large language models that can answer questions about themselves. Tools for text to speech and speech to text enable the tree to talk with participants without the necessity of text input and output. The general knowledge of AI makes it ready to answer not only possible unexpected questions, but also follow up ones.

A more interactive and playful approach to learning might lead to better comprehension and knowledge retention as other studies suggest [34]. A conversation between a human and a tree allows the user to ask for clarification, or to adapt the technicality of the conversation based on the user's speech. More advanced AI are capable to, in addition to answering questions correctly, interpreting a character, with correct usage of wordplay and even puns related to trees, which contributes to the immersion of the experience.

Figure 1 presents a chatbot-integrated holographic system capable of generating auditory and visual responses through a holographic tree to enhance user interaction. The system initiates with a spoken user input received by a microphone and transmitted in an audio stream via Wi-Fi to the Access Point (AP). The AP subsequently retransmits it to the embedded system. The user input is then converted into text through a voice-to-text translator module. This text serves as the input for the Chatbot. The chatbot's core comprises a language model that analyzes and interprets the input and generates a response based on NLP algorithms. By evaluating the probability distribution of subsequent words, the model ensures conversational coherence and contextual relevance.

The text response is transformed into speech using a text-to-voice module, creating an auditory interaction. Concurrently, the system generates a holographic tree image, and the audio data is transmitted to the speakers over a Wi-Fi network from the embedded system with synchronized transmission to facilitate a conversation with the Chatbot-integrated holographic tree. The holographic tree is animated to match the output speech. The system is proposed to be viewed in an indoor environment, so when the holographic projector is not placed in the same room as in the Wireless Access point, other considerations due to wall loss must be taken into account [35][36]. Overall, the theoretical implications of this system are significant and support educational applications.

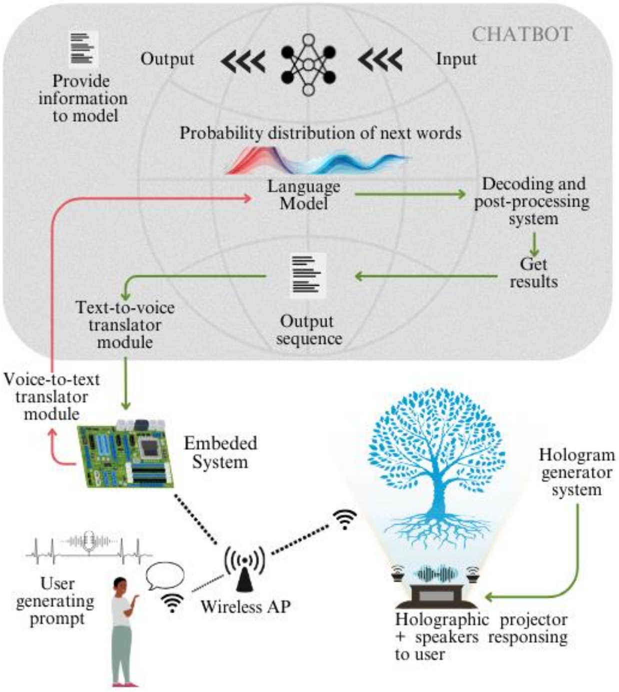

Figure 1. Illustration of the interaction between a user and a chatbot-integrated tensor hologram in a tree form.

Figure 2 represents a communication algorithms flowchart to illustrate the interaction between a user and a holographic system (in this case, a holographic tree). During the initialization phase, the system initiates the interaction and receives and interprets user input. Upon receiving user input, the system proceeds to the system processing stage, wherein NLP and speech recognition are utilized to process the user input, which may be a question or a command. User inputs can be as straightforward as: "Hello, can you tell me about your life as an orange tree?". The subsequent step, "Holographic tree response?", is the point at which the system evaluates whether it can generate a response to the user's input. If a response can be generated, the system proceeds to provide the user with a visual holographic response, which may be factual, educational, or procedural, based on the information retrieved from its database. If the user input is excessively complex or intricate, the system will propose that the user reformulate the prompt. Should the user decline, the system will proceed directly to the finalization stage to conclude the interaction without generating a response. If the user opts to proceed with a new prompt or input, the system will resume the cycle from the user input stage.

During the holographic tree response stage, the system creates an immersive volumetric 3D hologram or tensor hologram, as previously explained. The system's response is adaptive, dynamic, and interactive, enhancing user experience through engagement. Following this stage, the user has the option to continue the interaction or terminate it. Should the user wish to continue, the system loops back to the input stage and maintains the flow of interaction, leading to deeper engagement. However, if the user opts to end the interaction, the system transitions to the finalization stage, concluding the cycle. This design enables the system to process various types of queries, including factual and complex questions.

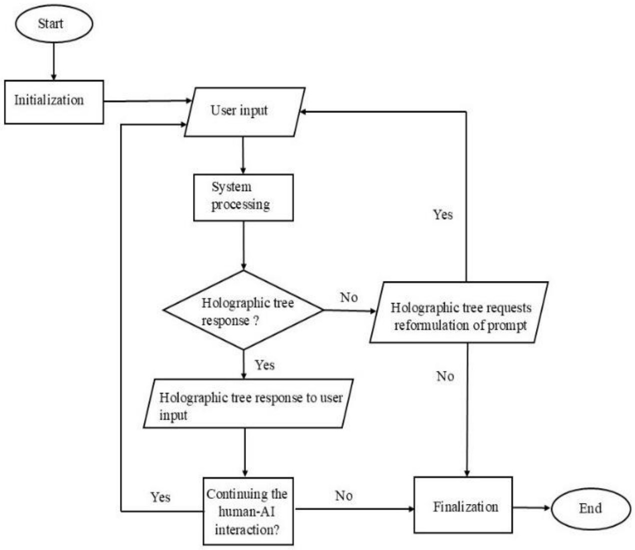

Figure 2. Communication algorithms flowchart framework between a user and a holographic tree.

It is a versatile system applicable to diverse domains and topics. To contribute with immersion, text to speech tools have also evolved to better pronounce words, add intonation, pauses and stress to the voice. Neural networks are also employed to this task, as they are capable of generalizing patterns that are not always present on the learning phase [37]. Advancements were also made with multilingual models, an extremely useful feature in our use case since LLM are capable of synthesizing text in multiple languages [38]. Those same models can also simulate different voices from short audio files, to add variety for different types of trees.

By combining those three consolidated technologies with holograms, it is possible to build a prototype of the proposed system and test its performance based on some metrics: answer correctness, its preciseness and character impression.

Other metrics, such as response time were considered, but all tested models presented near-real time answers, sometimes even faster than human interaction timings, thus it was not measured. This study conducted evaluations on three pertinent and freely accessible large language models: OpenAI's ChatGPT, Google's Gemini, and Microsoft's Copilot. The same set of prompts were input across all of them to avoid inconsistencies. The models were asked to "Pretend that you are an apple tree that talks. I'm going to ask you questions about your biology and you should answer as you were this tree". Afterwards, the three models were asked a series of questions on the subject.

All the models were able to answer the questions correctly. However, only ChatGPT and Microsoft Copilot played a role of a talking tree. Google Gemini answered in the first person, as requested, but did not simulate the ludic text of a cartoonish tree.

As an example, Table 1 presents the answer to the prompt mentioned in the last paragraph. Questions about apple trees were made, from simple ones, such as “What varieties of apple trees exist”, to more technical ones: “What amount of organic matter in the soil is necessary for the proper development of the apple tree and its fruit?” The AIs could answer both types of questions precisely, with no contradiction between them.

On average, the answers from the three systems were two paragraphs long. Copilot had more succinct answers and GPT the longest ones. None of them had single-line answers, even for the most direct questions, i.e., “How much water do your need to grow healthily?”. Overall, the answers are the length expected from an informative conversation.

IV. SIMULATION RESULTS

Figure 3 represents the recorded time measurements for each module during the testing phase. The elements are ordered according to their occurrence in the proposed interaction. Initially, the Speech-to-Text (STT) delay represents the time between the conclusion of human speech and the completion of its transcription. Subsequently, the GPT Start to Answer delay indicates the interval between prompt input and the initial output from GPT.

TABLE I. ANSWERS TO THE INITIAL PROMPT

Model	Answer
Chat GPT	Ah, welcome beneath my branches! I am a humble apple tree, deeply rooted in the soil, stretching my limbs toward the sky. What curiosities do you bring? Ask away, and I shall answer as best as a tree can!
Gemini	Okay, I'm ready to be an apple tree! Ask me anything you'd like to know about my life.
Copilot	Alright, I'm an apple tree! My branches are adorned with lush green leaves, and I bear delicious apples. Ask away, and I'll do my best to share the secrets of my tree-ish life with you! 🌳🍏🍎

Third, the total time for a complete answer represents the duration required for the conclusion of GPT operation. This period is not critical for application, as the Text-to-Speech (TTS) module can commence operation as soon as the first phrase is available. Lastly, the TTS Start Delay denotes the time between text input and the initiation of audio output.

Lastly, the TTS Start Delay denotes the time between text input and the initiation of audio output. It is noteworthy that the entire system can exhibit rapid response times to the user due to the potential for task parallelization. The STT module operates concurrently with user speech, resulting in its delay being perceptible only upon the cessation of speech. Similarly, the GPT delay is noticeable only until the completion of the first phrase, at which point, in conjunction with the TTS delay, the system will begin vocalization. The GPT completes the entire answer in approximately 14 seconds, which is significantly faster than the conclusion of TTS.

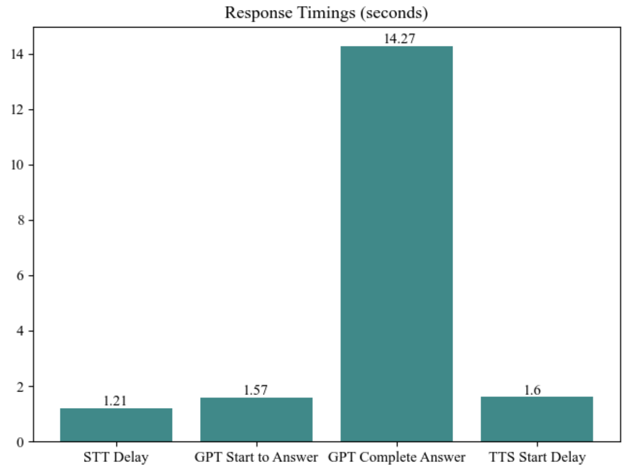

Figure 3. Measured response times for STT, GPT and TTS modules.

Consequently, it can be inferred that the response time delays are sufficiently low to maintain the fluidity of human-like conversation.

As previously noted by scholars [22], transmission delay has a significant impact on user engagement and satisfaction, particularly in the context of enhancing agricultural management efficiency. This graphical representation leads to the conclusion that special attention must be directed towards delay time when incorporating AI and holographic technology in intelligent agriculture to ensure an efficiency in human-AI interactions.

V. CONCLUSION

In this article, we propose an interactive hologram system to present information about plants to humans. This system enables dynamic interaction between humans and machines to learn more effectively, in a ludic way. To do so, four core technologies must be combined: holograms, large language models, text-to-speech and speech-to-text tools. Holograms provide three-dimensional images from the plants studied for better visualization and comprehension of the physical aspects of the tree, in addition to better immersing the user in their learning experience.

Large language models are an efficient way of garnering information, organizing and presenting it to a human in a conversation in the most natural way. Their capabilities of synthesizing text have been used in several areas and can help swiftly accessing information combined from various sources. Tests were conducted with them to extract information about apple trees. The results show how not only do they return precise, correct answers, but also can interpret a role of a cartoonish talking tree, enhancing the experience.

Text-to-speech tools are responsible for receiving the output of the LLM and synthesizing voice. It is crucial for the user experience to have, in addition to the correct pronunciation, intonation, pauses and stress capabilities.

Neural networks have also been employed in the state-of-the-art models due to their potential of extracting patterns from data and generalizing for unseen information. It is also possible for a single network to speak multiple languages, featured with the LLMs.

The experiment is promising, and more research is important to better implement it. For future work, more advanced features could be considered, such as interaction between two plants that have symbiotic relationships. Open source LLM models are also considered to better adjust them to the task. In addition to it, designing tree models with faces that have moving mouths could be an important step towards its implementation.

In the context of holography, a critical consideration for future development is the resolution of current technical constraints in data transmission and latency to facilitate holographic communication and the implementation of interactive holographic projections, especially in digital agriculture. This has consistently proven to be a significant factor during system evaluations when measuring STT, TTS, and GPT modules in human-AI interactions. Our future work will be focused on improving the GPT response time and testing other Conversational AI and AI Chatbots.

ACKNOWLEDGMENT

This work has been partially funded by the "Generalitat Valenciana" through the “Programa Investigo” project INVEST/2022/467, partially supported by Project TED2021-131040B-C31 funded by MICIU/AEI/10.13039/501100011033 and by European Union NextGenerationEU/PRTR, and partially supported by CAPES from Brazil Federal Government under project 88881.933610/2024-01

REFERENCES

[1] M. Escribà-Gelonch *et al.*, “Digital Twins in Agriculture: Orchestration and Applications,” *J Agric Food Chem*, vol. 72, no. 19, pp. 10737–10752, May 2024, doi: 10.1021/acs.jafc.4c01934.

[2] N. Peladarinos *et al.*, “Enhancing Smart Agriculture by Implementing Digital Twins: A Comprehensive Review,” *Sensors*, vol. 23, no. 16, p. 7128, Aug. 2023, doi: 10.3390/s23167128.

[3] T. Alahmad, M. Neményi, and A. Nyéki, “Applying IoT Sensors and Big Data to Improve Precision Crop Production: A Review,” *Agronomy*, vol. 13, no. 10, p. 2603, Oct. 2023, doi: 10.3390/agronomy13102603.

[4] L. A. Puntel, L. J. Thompson, and T. Mieno, “Leveraging digital agriculture for on-farm testing of technologies,” *Frontiers in Agronomy*, vol. 6, Mar. 2024, doi: 10.3389/fagro.2024.1234232.

[5] S. O. Araújo, R. S. Peres, J. C. Ramalho, F. Lidon, and J. Barata, “Machine Learning Applications in Agriculture: Current Trends, Challenges, and Future Perspectives,” *Agronomy*, vol. 13, no. 12, p. 2976, Dec. 2023, doi: 10.3390/agronomy13122976.

[6] R. P. W. A. Dilrukshi *et al.*, “Precision Agricultural Technologies for enhancing crop productivity: A way forward to Sri Lankan Agriculture,” *Sri Lanka Journal of Food and Agriculture*, vol. 7, no. 2, pp. 23–42, Dec. 2021, doi: 10.4038/sljfa.v7i2.98.

[7] O. Calicioglu, A. Flammini, S. Bracco, L. Bellù, and R. Sims, “The Future Challenges of Food and Agriculture: An Integrated Analysis of Trends and Solutions,” *Sustainability*, vol. 11, no. 1, p. 222, Jan. 2019, doi: 10.3390/su11010222.

[8] W. P. Falcon, R. L. Naylor, and N. D. Shankar, “Rethinking Global Food Demand for 2050,” *Popul Dev Rev*, vol. 48, no. 4, pp. 921–957, Dec. 2022, doi: 10.1111/padr.12508.

[9] I. Sandeepanie, “Big Data Analytics in Agriculture,” pp. 1–8, Sep. 2020, doi: 10.13140/RG.2.2.25154.81604.

[10] G. Lv *et al.*, “Blockchain-Based Traceability for Agricultural Products: A Systematic Literature Review,” *Agriculture*, vol. 13, no. 9, p. 1757, Sep. 2023, doi: 10.3390/agriculture13091757.

[11] P. Xu, J. Lee, J. R. Barth, and R. G. Richey, “Blockchain as supply chain technology: considering transparency and security,” *International Journal of Physical Distribution & Logistics Management*, vol. 51, no. 3, pp. 305–324, Jan. 2021, doi: 10.1108/IJPDLM-08-2019-0234.

[12] A. Srivastava and J. Prakash, “Techniques, Answers, and Real-World UAV Implementations for Precision Farming,” *Wirel Pers Commun*, vol. 131, pp. 2715–2746, Aug. 2023, doi: 10.1007/s11277-023-10577-z.

[13] M. Jenkins and D. E. Block, “A Review of Methods for Data-Driven Irrigation in Modern Agricultural Systems,” *Agronomy*, vol. 14, no. 7, p. 1355, Jun. 2024, doi: 10.3390/agronomy14071355.

[14] C. Maraveas, “Incorporating Artificial Intelligence Technology in Smart Greenhouses: Current State of the Art,” *Applied Sciences*, vol. 13, no. 1, p. 14, Dec. 2022, doi: 10.3390/app13010014.

[15] K. Rijswijk *et al.*, “Digital transformation of agriculture and rural areas: A socio-cyber-physical system framework to support responsibilisation,” *J Rural Stud*, vol. 85, pp. 79–90, Jul. 2021, doi: 10.1016/j.jrurstud.2021.05.003.

[16] M. Jacquot, J. B. Carcano, R. Giust, and L. Froehly, “I learned it through the hologram,” *Photoniques*, no. 119, pp. 31–35, Jun. 2023, doi: 10.1051/photon/202311931.

[17] S. Xu *et al.*, “Development of portable user-interactive holographic information collector for agricultural product markets,” *International Journal of Agricultural and Biological Engineering*, vol. 13, no. 3, pp. 143–153, 2020, doi: 10.25165/j.ijabe.20201303.5845.

[18] M. K. Bekele, R. Pierdicca, E. Frontoni, E. S. Malinverni, and J. Gain, “Electronic display system for computational holography,” *Journal on Computing and Cultural Heritage*, vol. 11, no. 2, pp. 1–36, Mar. 2018, doi: 10.1145/3145534.

[19] A. O. Alabi and S. M. Mutula, “Digital inclusion for visually impaired students through assistive technologies in academic libraries,” *Library Hi Tech News*, vol. 37, no. 2, pp. 14–17, Feb. 2020, doi: 10.1108/LHTN-11-2019-0081.

[20] S. Janai, T. Shreekanth, M. Chandan, and A. K. Abraham, “Speech-to-Speech Conversion,” *International Journal of Ambient Computing and Intelligence*, vol. 12, no. 1, pp. 184–206, 2021, doi: 10.4018/IJACI.2021010108.

[21] T. B. Brown *et al.*, “Language Models are Few-Shot Learners,” pp. 1–75, May 2020, doi: 10.48550/arXiv.2005.14165.

[22] K. Kara, J. Lloret, O. Romero, and S. Sendra, “Performance Test of Holographic Video Communication System,” in *2024 International Conference on Multimedia Computing, Networking and Applications (MCNA)*, IEEE, Sep. 2024, pp. 15–20. doi: 10.1109/MCNA63144.2024.10703941.

[23] P. St-Hilaire *et al.*, “Electronic display system for computational holography,” *Society of Photo-Optical Instrumentation Engineers (SPIE)*, vol. 1212, no. Practical Holography IV, pp. 174–182, May 1990, doi: 10.1117/12.17980.

[24] T. Shimobaba *et al.*, “Deep-Learning Computational Holography: A Review,” *Frontiers in Photonics*, vol. 3, pp. 1–16, Mar. 2022, doi: 10.3389/fphot.2022.854391.

[25] T. Latychevskaia, “Iterative phase retrieval for digital holography: tutorial,” *Journal of the Optical Society of America A*, vol. 36, no. 12, pp. 31–40, Dec. 2019, doi: 10.1364/JOSAA.36.000D31.

[26] Y. Gao and L. Cao, “Iterative projection meets sparsity regularization: towards practical single-shot quantitative phase imaging with in-line holography,” *Light: Advanced Manufacturing*, vol. 4, no. 1, 2023, doi: 10.37188/lam.2023.006.

[27] S. Mustafi and T. Latychevskaia, “Fourier Transform Holography: A Lensless Imaging Technique, Its Principles and Applications,” *Photonics*, vol. 10, no. 2, pp. 1–28, Feb. 2023, doi: 10.3390/photonics10020153.

[28] R. Zhu, L. Chen, and H. Zhang, “Computer holography using deep neural network with Fourier basis,” *Opt Lett*, vol. 48, no. 9, pp. 2333–2336, May 2023, doi: 10.1364/OL.486255.

[29] O. Shigematsu, M. Naruse, and R. Horisaki, “Computer-generated holography with ordinary display,” *Opt Lett*, vol. 49, no. 8, pp. 1876–1879, 2024, doi: 10.1364/OL.516005.

[30] G. Situ, “Deep holography,” *Light: Advanced Manufacturing*, vol. 3, no. 2, pp. 278–300, 2022, doi: 10.37188/lam.2022.013.

[31] Y. Huang *et al.*, “Toward Holographic Video Communications: A Promising AI-Driven Solution,” *IEEE Communications Magazine*, vol. 60, no. 11, pp. 82–88, Oct. 2022, doi: 10.1109/MCOM.001.220021.

[32] X. Huang, Y. Zhou, H. Liang, and J. Zhou, “Binocular near-eye augmented reality enabled by full utilization of functional computer generated hologram,” *Opt Lasers Eng*, vol. 176, no. 108115, pp. 1–7, May 2024, doi: 10.1016/j.optlaseng.2024.108115.

[33] F. Lareyre *et al.*, “Large language models and artificial intelligence chatbots in vascular surgery,” Sep. 01, 2024, *W.B. Saunders*. doi: 10.1053/j.semvascsurg.2024.06.001.

[34] Z. Zhang and X. Huang, “The impact of chatbots based on large language models on second language vocabulary acquisition.,” *Heliyon*, vol. 10, no. 3, Feb. 2024, doi: 10.1016/j.heliyon.2024.e25370.

[35] M. Garcia, C. Martinez, J. Tomas, and J. Lloret, “Wireless Sensors Self-Location in an Indoor WLAN Environment,” in *2007 International Conference on Sensor Technologies and Applications (SENSORCOMM 2007)*, IEEE, Oct. 2007, pp. 146–151. doi: 10.1109/SENSORCOMM.2007.4394912.

[36] M. Garcia-Pineda, J. Tomás, F. Boronat, and J. Lloret, “The Development of Two Systems for Indoor Wireless Sensors Self-location,” *Ad Hoc Sens. Wirel. Networks*, vol. 8, pp. 235–258, Dec. 2009, [Online]. Available: https://www.researchgate.net/publication/220419345_The_Development_of_Two_Systems_for_Indoor_Wireless_Sensors_Self-location. [retrieved: October, 2024]

[37] V. R. Reddy and K. S. Rao, “Two-stage intonation modeling using feedforward neural networks for syllable based text-to-speech synthesis,” *Comput Speech Lang*, vol. 27, no. 5, pp. 1105–1126, Aug. 2013, doi: 10.1016/j.csl.2013.02.003.

[38] E. Casanova *et al.*, “XTTS: a Massively Multilingual Zero-Shot Text-to-Speech Model,” Jun. 2024, [Online]. Available: https://arxiv.org/abs/2406.04904. [retrieved: October, 2024]