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Deep Learning Based Augmented Reality for 3D Object Recognition

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Abstract: Augmented Reality (AR) technology is being widely adopted in various fields such as education, entertainment, and creativity. However, there are still some challenges to be overcome in recognizing and rendering three-dimensional (3D) objects accurately and in real-time. We implemented an AR system that utilizes deep learning techniques to recognize 3D objects with improved accuracy levels. Our approach involved training a Convolutional Neural Network (CNN) model using 3D object datasets captured from different viewpoints. The development included designing the network architecture, training the model, evaluating its accuracy, and integrating it into an AR platform based on Unity 3D and Vuforia SDK. The results indicated that the system could achieve recognition of the 3D objects with an average accuracy of 93.7%, precision of 92.4%, and recall of 91.8%, all while keeping response times below 0.8 seconds. Objects with complex geometries like cars and chairs had recognition rates above 94%, while those with similar textures had lower accuracy because of detailed surface complexities. It allows stable interactive visualization of objects in augmented reality even under different lighting conditions and camera angles. Combining deep learning with AR improves the quality of object recognition and provides a more realistic interactive experience. This paper discusses the advances made in AR technology toward better adaptability and efficiency, which can be applied to interactive education, industrial simulation, architecture, and medical fields.

Keywords: Augmented Reality; Deep Learning; Object Recognition; 3D; Convolutional Neural Network.

1. Introduction

Information and communication technology has brought developments that have changed the way people relate with the digital world. Among fast-growing technologies, Augmented Reality is a paradigm where virtual objects are integrated seamlessly into the real world in real time to create hybrid environments whereby digital information enhances physical reality. AR finds its application mostly in entertainment and gaming, but it has gained much traction in education, industry, healthcare, and marketing. By providing interactive immersive experiences, it increases the effectiveness of learning processes as well as improves efficiency in various work environments. Educational institutions are making use of AR by developing engaging learning materials that allow students to visualize complex concepts in three dimensions while industries utilize AR for training simulations, maintenance guidance, and quality control processes. In healthcare, AR helps surgeons during operations by overlaying critical patient data onto their field of view; in marketing brands create interactive campaigns allowing consumers to virtually experience products before purchase.

The main problem is that the system should identify objects accurately and quickly—especially three-dimensional (3D) objects—in changing and uncontrolled environments. Recognition of 3D objects is more complex than 2D image recognition since it involves understanding not only shape and texture but also spatial relationships between parts of an object from different viewpoints. The system must handle rotations, translations, scale variations, and partial occlusions while maintaining real-time performance. Traditional image processing-based methods using feature extraction techniques such as Scale-Invariant Feature Transform (SIFT) or Speeded Up Robust Features (SURF) often fail under changing lighting conditions with rotation of the object and changes in scale resulting in recognition outcomes that are less than optimal for practical deployment of AR systems. These conventional approaches rely on handcrafted features which do not generalize well across different categories of objects and varying environmental conditions; thus presenting a bottleneck problem for robust AR applications [1].

Recent advancements in artificial intelligence, particularly deep learning, have presented more adaptive and accurate methodologies for visual pattern recognition, inspiring innovative tactics to overcome some limitations of conventional approaches. Convolutional Neural Network algorithms have demonstrated their power in object detection and recognition based on complex visual features through the learning of hierarchical features. In contrast to feature engineering techniques that require manual design of features, CNNs automatically learn the most pertinent features from the data itself, allowing them to capture fine-grained patterns that are challenging to handcraft. The integration of CNN with AR is expected to improve system performance in real-time 3D object recognition by providing more realistic and interactive visual representations. Recent architectural advancements in deep learning, such as residual networks and attention mechanisms, have improved the accuracy and efficiency of object recognition systems so that these systems can run even on resource-constrained AR devices like smartphones and wearable headsets [2].

Earlier work has shown that applying CNN to 2D object recognition gives quite high accuracy; some models achieve human-level performance on benchmark datasets. The use of CNN for 3D objects in AR environments is an area where there is still relatively little application and much room for further development—especially concerning real-time processing challenges, computational efficiency, and robustness under varying environmental conditions. Some research has touched on applying deep learning toward AR applications but most studies focus on marker-based recognition or 2D image tracking which makes a gap because very little work has been done in markerless 3D object recognition that would function reliably under unconstrained real-world scenarios [3]. Our study involves developing a deep learning-based AR system for 3D object recognition wherein we attempt to improve the accuracy of recognition and speed up the rendering of objects into real environments. We train CNN models with different datasets of 3D objects from various angles and lighting conditions so as to generalize well onto new ones with different settings. We hope our results will encourage more adaptive and effective AR technology while opening up application opportunities across interactive education—where students get to play around with 3D models of historical artifacts or biological structures—industrial simulation training workers on complex machinery architecture visualizing building designs in situ medical applications surgical planning anatomy education Beyond just technical aspects our work offers broad practical benefits toward developing mixed reality-based technology bridging theoretical advances in deep learning consumer toward professional deployment in practical AR applications.

2. Related Work

Augmented Reality (AR) technology has significantly developed in the last decade, allowing the virtual objects to be integrated with the real world through cameras, smart phones, and head-mounted displays. AR systems possess three fundamental properties: interactivity, real-time processing capability, and integration within three-dimensional space [4]. The above capabilities have enabled AR applications in different domains such as education, healthcare, industrial training, and marketing. Wang *et al.* revealed that AR enhances visual inspection processes through knowledge-based deep learning by providing more immersive visualizations that improve user engagement and task performance 0. Even though advances have been made, accurate recognition and mapping of real-world objects especially 3D objects is still a challenge toward achieving precise alignment between virtual environments and physical environments.

The challenge of 3D object recognition arises from the requirement to identify objects based on their geometric shape, texture, and spatial structure under multiple variations such as rotation, view angle lighting condition scale variation. Raj *et al.* constructed an AR assembly assistance system which exposed increased complexity of 3D recognition over 2D approaches [6]. Traditional computer vision methods like Scale-Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF), which are based on handcrafted feature descriptors, often struggle with variations in the environment and occlusions. These limitations have led researchers to seek more flexible solutions based on artificial intelligence and deep learning techniques.

Deep learning architectures particularly Convolutional Neural Networks (CNNs) have revolutionized object recognition by learning hierarchical feature representations directly from raw data automatically. Kastner *et al.* proposed a calibration method for robotic AR environments based on 3D deep learning using depth sensor data which demonstrated that CNNs could extract visual features from low-level edges and textures to high-level semantic information [7]. Hsu *et al.* (2023) used deep learning object detection with AR for building defect inspection applying the AlexNet architecture achieving very high accuracy in structural anomaly identification [8]. These studies proved that CNN could outperform traditional methods in terms of accuracy as well as robustness when dealing with complex visual patterns.

Recent studies have attracted attention toward merging deep learning with AR for the purpose of enabling object recognition and tracking in real time. Rupa *et al.* applied augmented reality and object recognition to develop a system that detects the names of medicine drugs; their work proved that CNN-based AR systems are capable of recognizing as well as tracking objects with greater accuracy and stability [9]. Egipko *et al.* (2024) discussed object recognition based on deep learning in real time within augmented reality environments, which they applied to medical visualization, architectural design, and industrial simulation [10]. This work proved that deep learning is able to meet the computational requirements of real-time AR applications while still maintaining recognition accuracy among different categories of objects under various environmental conditions.

Yet several issues linger concerning 3D object recognition optimization for AR applications. Park *et al.* (2022) looked into self-training approaches for robust 3D object registration and task assistance, asserting that computational efficiency and user experience still need optimization, especially for resource-constrained mobile and wearable devices [11]. Lee *et al.* (2022) discussed multi-object recognition along with 3D position estimation in AR; they found a gap in methodology capable of handling multiple objects at the same time while keeping up real-time performance [12]. Even though considerable strides have been made by existing research through the application of deep learning to augmented reality, most studies are limited to controlled environments or specific application domains. We fill these gaps with our work on a generalized deep learning-based augmented reality system for 3D object recognition that seeks an optimal trade-off among accuracy, computational efficiency, and user experience across different real-world scenarios.

3. Research Method

This study employs an experimental approach aimed at developing and testing a deep learning-based Augmented Reality system capable of accurate and real-time 3D object recognition [13]. The research process was conducted in several stages: data collection, deep learning model design, model training, integration with the AR platform, and system performance testing [14].

3.1 Data Collection

The dataset consists of 3D objects from various categories, including household appliances, vehicles, and educational objects. The datasets were obtained from open sources such as ModelNet40 and supplemented with custom data created using Blender 3D modeling software. Each object was captured from multiple viewing angles with variations in lighting conditions and scale to increase data diversity and improve model generalization. The total dataset comprises 12,000 3D object images, divided into training data (80%, n=9,600) and test data (20%, n=2,400). Data preprocessing included normalization, resizing to 224×224 pixels, and augmentation techniques such as rotation, flipping, and brightness adjustment.

3.2 Deep Learning Model Design

The deep learning model employs a Convolutional Neural Network (CNN) architecture specifically designed for 3D object recognition. The network architecture consists of several main layers:

1) Convolutional layers to extract hierarchical features from input images, starting from low-level edges and textures to high-level semantic representations,
2) Pooling layers to reduce spatial dimensions while retaining salient features, thereby decreasing computational complexity,
3) Fully connected layers to perform final classification of object categories based on extracted features.

The model was implemented using TensorFlow 2.10 and PyTorch 1.12 frameworks. Training hyperparameters were determined through preliminary experiments, with a learning rate of 0.001, batch size of 32, and 50 training epochs. The network architecture includes five convolutional blocks, each followed by batch normalization and ReLU activation functions.

3.3 Model Training

The training process was executed on a machine with Intel Core i7-11700K processor, NVIDIA GeForce RTX 3070 GPU (8GB VRAM), and 16 GB RAM. During training, optimization was performed using the Adam Optimizer algorithm with β_1=0.9 and β_2=0.999, and categorical cross-entropy as the loss function. To prevent overfitting, several regularization techniques were applied, including data augmentation, dropout (rate=0.5) on fully connected layers, and early stopping with a patience of 10 epochs. Training convergence was monitored through validation loss and accuracy metrics recorded after each epoch.

3.4 Integration with AR Platform

The trained CNN model was integrated with the AR platform using Unity 3D (version 2021.3) and Vuforia SDK (version 10.5). The system architecture enables the device's camera to capture real-world objects in real-time, which are then processed by the CNN model for classification. Upon successful recognition, the system renders and overlays the corresponding virtual 3D representation onto the physical object, allowing users to view virtual objects seamlessly integrated with their real environment. The integration pipeline includes frame capture, image preprocessing, model inference, and AR rendering, all optimized to maintain real-time performance at 30 frames per second.

3.5 System Performance Testing

Testing was conducted to evaluate both the accuracy of 3D object recognition and overall system performance in an AR environment. The evaluation employed two approaches:

1) Accuracy Evaluation: Measuring classification accuracy, precision, recall, and F1-score based on the test dataset to assess the model's ability to correctly identify object categories.
2) Performance Evaluation: Measuring system response time (latency), frame rate, and stability of 3D object tracking and rendering in AR to ensure smooth user experience.

Additionally, user testing was conducted involving 20 participants (12 males, 8 females, aged 20-35 years) to assess interactive aspects and user experience. Participants performed object recognition tasks in various lighting conditions and viewing angles. Test results were analyzed quantitatively using accuracy, precision, recall, F1-score, and response time metrics, as well as qualitatively through user satisfaction questionnaires employing a 5-point Likert scale covering aspects of ease of use, recognition accuracy, visual quality, and overall satisfaction.

4. Result and Discussion

4.1 Results

The developed Convolutional Neural Network (CNN) model was trained using a 3D object dataset comprising 12,000 images over 50 epochs. The training process achieved a training accuracy of 96.2% and a validation accuracy of 93.7%. Figure 1 shows the training and validation accuracy curves throughout the training process, demonstrating steady convergence without significant fluctuations. The relatively small gap between training and validation accuracy (2.5%) indicates that the model did not experience significant overfitting, which was achieved through the implementation of data augmentation techniques (rotation, flipping, brightness adjustment) and dropout regularization (rate=0.5) on fully connected layers. Testing was conducted on 2,400 images from the test dataset. The system successfully recognized 3D objects with an overall accuracy of 93.7%, precision of 92.4%, recall of 91.8%, and F1-score of 92.1%. Table 1 presents detailed performance metrics for each object category. Objects with distinctive geometric features, such as cars and chairs, demonstrated higher recognition rates (95.2% and 94.5% respectively), while objects with similar textures and shapes, such as cups and vases, exhibited lower accuracy (91.7% and 91.3% respectively).

Table 1. Results of 3D Object Recognition Testing Using CNN in AR

Object Category	Test Data Amount	Accuracy (%)	Precision (%)	Recall (%)	Response Time (s)
Car	400	95.2	94.6	93.8	0.75
Chair	400	94.5	93.2	92.7	0.78
Table	400	93.6	92.5	91.8	0.81
Cup	400	91.7	90.4	89.6	0.83
Flower Vase	400	91.3	90.1	89.2	0.85
Average	2,400	93.7	92.4	91.8	0.80

Following integration with Unity 3D (version 2021.3) and Vuforia SDK (version 10.5), the system demonstrated real-time object recognition and virtual object rendering capabilities. The average response time from object capture to virtual object display was 0.80 seconds, with individual object categories ranging from 0.75 to 0.85 seconds. The system maintained stable performance at 30 frames per second during AR rendering. Figure 2 illustrates the system response time distribution across different object categories. Testing under various environmental conditions revealed that the system maintained high recognition accuracy (>90%) under normal and bright lighting conditions. However, under extremely low-light conditions (below 50 lux), recognition accuracy decreased to approximately 87%. Virtual object tracking and rendering remained stable across different camera angles (0° to 45° tilt) and distances (0.5 to 3 meters from the object). User testing involved 20 participants (12 males, 8 females, aged 20-35 years) who performed object recognition tasks using the AR application in everyday scenarios. Participants completed a satisfaction questionnaire using a 5-point Likert scale (1=very dissatisfied, 5=very satisfied). Results showed that 85% of participants (n=17) expressed satisfaction with the system's accuracy and response speed, while 15% (n=3) indicated that improvements were needed for low-light performance. The interactive experience aspect received an average score of 4.3 out of 5.0, with specific ratings as follows: ease of use (4.4), recognition accuracy (4.2), visual quality (4.3), and overall satisfaction (4.3). Figure 1 presents the detailed user satisfaction ratings across different evaluation criteria.

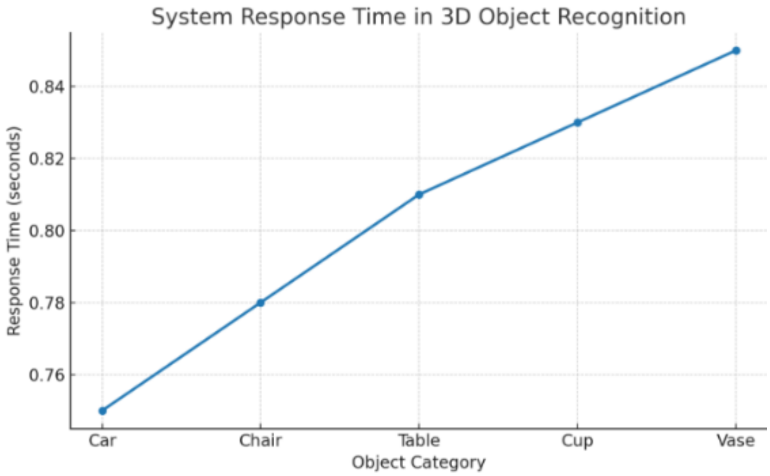

Figure 1. System Response Graph

4.2 Discussion

The CNN model achieved strong performance with 93.7% test accuracy, demonstrating effective learning of 3D object features from the training dataset. The small gap between training accuracy (96.2%) and validation accuracy (93.7%) confirms that the regularization techniques employed—data augmentation and dropout—successfully prevented overfitting and improved model generalization. Hsu *et al.* (2023) reported similar accuracy levels using deep learning for object detection in AR applications, which aligns with the findings of this study [8]. The model's ability to maintain consistent performance across validation and test datasets suggests that it can generalize well to unseen data, which is crucial for real-world AR applications. Analysis of recognition performance across different object categories reveals that geometric complexity and texture distinctiveness significantly influence recognition accuracy. Objects with unique geometric features and well-defined edges, such as cars (95.2%) and chairs (94.5%), achieved higher recognition rates compared to objects with similar shapes and textures, such as cups (91.7%) and vases (91.3%). This performance variation can be attributed to the hierarchical feature learning process in CNNs, where distinctive geometric patterns are more easily captured and differentiated by convolutional layers. Objects with similar textures pose challenges because the model relies heavily on surface details that may appear ambiguous when viewed from certain angles or under varying lighting conditions. Raj *et al.* (2024) noted that texture similarity remains a significant challenge in 3D object recognition systems, which is consistent with the findings of this study [6]. To address these limitations, future work could incorporate multi-view recognition approaches or integrate depth information using RGB-D sensors. Park *et al.* (2020) suggested that RGB-D data provides additional spatial cues that help distinguish between visually similar objects, which could improve recognition accuracy for texture-similar categories [3].

The system's average response time of 0.80 seconds falls within acceptable ranges for interactive AR applications. Egipko *et al.* (2024) established that response times below 1.0 second provide satisfactory user experience in real-time AR systems [10]. The relatively consistent response times across object categories (0.75-0.85 seconds) indicate that the CNN model maintains stable computational performance regardless of object complexity. The system successfully maintained 30 frames per second during AR rendering, ensuring smooth visual integration of virtual objects with the physical environment. However, the system's performance degradation under low-light conditions (accuracy dropping to 87%) highlights a common challenge in computer vision systems. Poor lighting reduces image quality and feature visibility, making it difficult for the CNN to extract discriminative features. Wang *et al.* (2021) noted that environmental factors significantly impact AR system performance, which aligns with the limitations observed in this study 0. Potential solutions include implementing adaptive image enhancement techniques, such as histogram equalization or low-light image enhancement algorithms, before feeding images to the CNN model.

The high user satisfaction rating (4.3 out of 5.0) and positive feedback from 85% of participants indicate that the system provides an engaging and effective AR experience. Users appreciated the system's accuracy and responsiveness, which are critical factors for maintaining immersion in AR applications. The interactive experience scores suggest that the system successfully integrates virtual objects with the real environment in a manner that feels natural and intuitive to users. The 15% of participants who expressed concerns about low-light performance provide valuable feedback for system improvement. This user input corroborates the quantitative performance data showing accuracy degradation under poor lighting conditions. Addressing these concerns through technical improvements would enhance the system's robustness and expand its applicability to diverse real-world scenarios, including indoor environments with variable lighting. The successful integration of CNN-based 3D object recognition with AR demonstrates the feasibility of deploying deep learning models in real-time interactive applications. The system's performance metrics—93.7% accuracy and 0.80-second response time—establish a baseline for practical AR applications in education, industrial training, and consumer experiences. Li *et al.* (2021) and Gupta *et al.* (2023) discussed the growing body of research on deep learning-enabled AR systems, to which these results contribute [13][14]. Future research should focus on several key areas: (1) improving recognition accuracy for texture-similar objects through multi-modal feature fusion, (2) enhancing low-light performance using advanced image preprocessing techniques, (3) optimizing computational efficiency for deployment on mobile and wearable devices with limited processing power, and (4) expanding the object dataset to include more diverse categories and real-world variations. Additionally, exploring lightweight CNN architectures, such as MobileNet or EfficientNet, could reduce computational requirements while maintaining recognition accuracy, making the system more accessible for resource-constrained devices.

5. Conclusion

This paper presented a deep learning-based Augmented Reality system for 3D object recognition with high accuracy and low latency. Experimental results showed that the trained CNN model on the 3D object dataset achieved an average accuracy of 93.7%, precision of 92.4%, recall of 91.8%, and F1-score of 92.1% with an average response time of 0.80 seconds. These results indicated that integrating deep learning into AR can significantly enhance the performance of 3D object recognition while providing users with a realistic and interactive experience. The system also kept stable performance at 30 frames per second during AR rendering, which ensured smooth visual integration between virtual objects and the physical environment.

Object categories with complex shapes and distinctive visual features, such as cars (95.2%) and chairs (94.5%), achieved the best recognition performance. In contrast, objects with similar surface textures, such as cups (91.7%) and vases (91.3%), resulted in higher misclassification rates, indicating that surface detail and texture similarity remain significant challenges in 3D object recognition. Low-light conditions negatively affected system accuracy, with performance degrading to approximately 87% under extremely poor lighting (below 50 lux). User testing involving 20 participants yielded positive results, with 85% expressing satisfaction with the system's accuracy and responsiveness, and an overall interactive experience rating of 4.3 out of 5.0.

This work is a step toward more dynamic and practical AR technology for real-time 3D object recognition. The performance metrics set by this system can be considered baseline parameters for real-world educational AR applications, industrial training simulations, or consumer experiences seeking augmented reality solutions in their products or services. Future work should focus on several key areas: (1) employing more advanced network architectures such as 3D-CNN or PointNet to better capture spatial features of 3D objects; (2) implementing adaptive image enhancement techniques such as histogram equalization or low-light enhancement algorithms to overcome limitations under varying environmental conditions; (3) integrating multi-view recognition approaches or RGB-D sensors to improve accuracy for texture-similar objects; and finally (4), optimizing computational efficiency through lightweight architectures like MobileNet or EfficientNet for deployment on resource-constrained mobile and wearable devices With further development potential exists within this system toward broad implementation across interactive education industrial simulations architectural visualization medical training consumer AR applications.

References

[1] Ghasemi, Y., Jeong, H., Choi, S. H., Park, K. B., & Lee, J. Y. (2022). Deep learning-based object detection in augmented reality: A systematic review. *Computers in Industry*, *139*, 103661. https://doi.org/10.1016/j.compind.2022.103661

[2] Park, K. B., Kim, M., Choi, S. H., & Lee, J. Y. (2020). Deep learning-based smart task assistance in wearable augmented reality. *Robotics and Computer-Integrated Manufacturing*, *63*, 101887. https://doi.org/10.1016/j.rcim.2019.101887

[3] Park, K. B., Choi, S. H., Kim, M., & Lee, J. Y. (2020). Deep learning-based mobile augmented reality for task assistance using 3D spatial mapping and snapshot-based RGB-D data. *Computers & Industrial Engineering*, *146*, 106585. https://doi.org/10.1016/j.cie.2020.106585

[4] Cheng, Q., Zhang, S., Bo, S., Chen, D., & Zhang, H. (2020). Augmented reality dynamic image recognition technology based on deep learning algorithm. *IEEE Access*, *8*, 137370–137384. https://doi.org/10.1109/ACCESS.2020.3012130

[5] Wang, S., Zargar, S. A., & Yuan, F. G. (2021). Augmented reality for enhanced visual inspection through knowledge-based deep learning. *Structural Health Monitoring*, *20*(1), 426–442. https://doi.org/10.1177/1475921720976986

[6] Raj, S., Murthy, L. R. D., Shanmugam, T. A., Kumar, G., Chakrabarti, A., & Biswas, P. (2024). Augmented reality and deep learning based system for assisting assembly process. *Journal on Multimodal User Interfaces*, *18*(1), 119–133. https://doi.org/10.1007/s12193-023-00428-3

[7] Kastner, L., Frasineanu, V. C., & Lambrecht, J. (2020). A 3D-deep-learning-based augmented reality calibration method for robotic environments using depth sensor data. *Proceedings - IEEE International Conference on Robotics and Automation*, 1135–1141. https://doi.org/10.1109/ICRA40945.2020.9197155

[8] Hsu, S. H., Hung, H. T., Lin, Y. Q., & Chang, C. M. (2023). Defect inspection of indoor components in buildings using deep learning object detection and augmented reality. *Earthquake Engineering and Engineering Vibration*, *22*(1), 41–54. https://doi.org/10.1007/s11803-023-2152-5

[9] Rupa, C., Srivastava, G., Ganji, B., Tatiparthi, S. P., Maddala, K., Koppu, S., & Chun-Wei Lin, J. (2022). Medicine drug name detection based object recognition using augmented reality. *Frontiers in Public Health*, *10*, 881701. https://doi.org/10.3389/fpubh.2022.881701

[10] Egipko, V., Zhdanova, M., Gapon, N., Voronin, V. V., & Semenishchev, E. A. (2024). Real-time deep learning-based object recognition in augmented reality. *Proceedings of SPIE*, *13000*, 171–177. https://doi.org/10.1117/12.3024957

[11] Park, K. B., Choi, S. H., & Lee, J. Y. (2024). Self-training based augmented reality for robust 3D object registration and task assistance. *Expert Systems with Applications*, *238*, 122331. https://doi.org/10.1016/j.eswa.2023.122331

[12] Lee, T., Jung, C., Lee, K., & Seo, S. (2022). A study on recognizing multi-real world object and estimating 3D position in augmented reality. *The Journal of Supercomputing*, *78*(5), 7509–7528. https://doi.org/10.1007/s11227-021-04161-0

[13] Li, V., Amponis, G., Nebel, J.-C., Argyriou, V., Lagkas, T., & Sarigiannidis, P. (2021). Object recognition for augmented reality applications. *Azerbaijan Journal of High Performance Computing*, *4*(1), 15–28. https://doi.org/10.32010/26166127.2021.4.1.15.28

[14] Gupta, Y. P., Mukul, & Gupta, N. (2023). Deep learning model based multimedia retrieval and its optimization in augmented reality applications. *Multimedia Tools and Applications*, *82*(6), 8447–8466. https://doi.org/10.1007/s11042-022-13555-y.