ISSN: 2454-9940

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

E-Mail :
editor.ijasem@gmail.com
editor@ijasem.org

www.ijasem.org

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940

www.ijasem.org

Vol 18, Issue 2, 2024

GESTURE RECOGNITION FEDERATED LEARNING APPROACHES IN EDGE COMPUTING

[1]M Sreenivasu, [2]D Ramesh, [3]V Sneha Latha, [4]T Sai Pavan Kumar, [5]S Lahari

[1]Associate Professor, [2]Assistant Professor, [345]UG Students

[1]msreenivasucse@giet.ac.in, [2]rameshdhulipudicse@giet.ac.in, [3]snehalatha0302@gmail.com, [4]saipavanyadav26@gmail.com, [5]laharisirigineedi2805@gmail.com

Department of Information Technology,

GIET Engineering College, Rajamahendravaram, Andhra Pradesh – 533 296.

ABSTRACT

Gesture recognition, a fundamental aspect of human-computer interaction, has witnessed substantial advancements through the application of deep learning techniques. Hand gesture recognition system received great attention in the recent few years because of its manifoldness applications and the ability to interact with machine efficiently through human computer interaction. This abstract provides an overview of the evolving landscape of gesture recognition systems driven by deep neural networks. Leveraging Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and their variants, these systems analyze visual, depth, or motion data to discern intricate hand or body gestures, enabling seamless interactions between humans and machines. This review delineates the diverse applications of deep learning-based gesture recognition across domains such as robotics, healthcare, virtual reality, and sign language translation. The utilization of multimodal data fusion, transfer learning, and temporal analysis techniques is explored, highlighting their significance in refining model accuracy and robustness.

Keywords: Gesture recognition, Deep learning techniques, Hand gesture recognition system, Human-computer interaction, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Multimodal data fusion.

INTRODUCTION

Gesture recognition, a pivotal aspect of human-computer interaction, has undergone significant transformations propelled by the integration of deep learning methodologies [1]. In recent years, hand gesture recognition systems have garnered substantial attention due to their diverse applications and their ability to facilitate efficient interaction between humans and machines [2]. These systems leverage sophisticated deep neural networks, particularly Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and their variations, to interpret complex visual, depth, or motion data and discern intricate hand or body gestures [3]. The seamless interaction between humans and machines facilitated by gesture recognition systems has sparked interest across various domains, including robotics, healthcare, virtual reality, and sign language translation [4].

The proliferation of deep learning-based gesture recognition systems has been fueled by advancements in computing technologies, particularly in edge computing [5]. Edge computing, characterized by decentralized processing capabilities at the network edge, offers several advantages for gesture recognition applications. By processing data closer to the source of generation, edge computing reduces latency, enhances real-time responsiveness, and alleviates bandwidth constraints [6]. Moreover, the distributed nature of edge computing enables efficient utilization of resources and supports context-awareness, which is crucial for enhancing the accuracy and robustness of gesture recognition models [7]. This review aims to provide an extensive overview of gesture recognition systems, with a specific focus on federated learning approaches in edge computing environments. Federated learning, a decentralized machine learning paradigm, has emerged as a promising approach for training gesture recognition models across distributed edge devices while preserving data privacy and security [8]. By leveraging federated learning, edge devices collaboratively learn a global model while keeping raw data localized, thereby addressing privacy concerns associated with centralized data processing [9]. The utilization of CNNs and RNNs in gesture recognition has enabled remarkable progress in

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT
ISSN2454-9940
www.ijasem.org
Vol 18, Issue 2, 2024

accurately interpreting complex hand and body movements [10]. CNNs excel at extracting spatial features from visual data, making them well-suited for tasks such as hand gesture recognition from image inputs [11]. On the other hand, RNNs, with their ability to capture temporal dependencies in sequential data, are effective for recognizing dynamic gestures captured through motion sensors or video streams [12]. The fusion of CNNs and RNNs in hybrid architectures further enhances the capabilities of gesture recognition systems by combining spatial and temporal information [13].

The applications of deep learning-based gesture recognition span diverse domains, each presenting unique challenges and opportunities. In robotics, gesture recognition enables intuitive human-robot interaction, facilitating tasks such as robot control, object manipulation, and collaborative assembly [14]. In healthcare, gesture recognition systems support applications ranging from rehabilitation exercises and assistive technologies for individuals with motor impairments to monitoring patient movements for early detection of abnormalities [15]. The integration of multimodal data fusion techniques enhances the robustness and reliability of gesture recognition systems by combining information from multiple sources, such as visual, depth, and inertial sensors [16]. Transfer learning techniques allow gesture recognition models to leverage knowledge gained from pre-trained models on large datasets, thereby improving performance and accelerating model development [17]. Temporal analysis methods, including recurrent neural networks and attention mechanisms, play a crucial role in capturing temporal dynamics and contextual information in gesture sequences, leading to more accurate recognition outcomes [18]. In summary, the evolution of gesture recognition systems driven by deep learning techniques has revolutionized human-computer interaction across various domains. The adoption of federated learning approaches in edge computing environments holds immense potential for advancing gesture recognition capabilities while addressing challenges related to data privacy and distributed learning. This review explores the landscape of gesture recognition, highlighting the significance of CNNs, RNNs, multimodal data fusion, transfer learning, and temporal analysis techniques in shaping the future of gesture-based interactions in edge computing environments.

LITERATURE SURVEY

Gesture recognition, a foundational element of human-computer interaction, has undergone profound advancements in recent years, driven by the application of deep learning techniques. The increasing interest in hand gesture recognition systems stems from their versatile applications and their efficacy in facilitating efficient interactions between humans and machines. This literature survey provides a comprehensive overview of the evolving landscape of gesture recognition systems driven by deep neural networks, with a focus on federated learning approaches in edge computing environments. Deep learning methodologies, particularly Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and their variants, have revolutionized the field of gesture recognition by enabling the analysis of visual, depth, or motion data to discern intricate hand or body gestures. CNNs, renowned for their ability to extract spatial features from visual data, are well-suited for tasks such as hand gesture recognition from image inputs. On the other hand, RNNs excel at capturing temporal dependencies in sequential data, making them effective for recognizing dynamic gestures captured through motion sensors or video streams. The fusion of CNNs and RNNs in hybrid architectures further enhances the capabilities of gesture recognition systems by combining spatial and temporal information.

The applications of deep learning-based gesture recognition span a wide range of domains, including robotics, healthcare, virtual reality, and sign language translation. In robotics, gesture recognition enables intuitive human-robot interaction, facilitating tasks such as robot control, object manipulation, and collaborative assembly. In healthcare, gesture recognition systems support applications such as rehabilitation exercises, assistive technologies for individuals with motor impairments, and monitoring patient movements for early detection of abnormalities. In virtual reality environments, gesture recognition enhances user immersion and interaction, enabling intuitive manipulation of virtual objects and environments. Moreover, in sign language translation, gesture recognition plays a pivotal role in bridging communication barriers between individuals who are deaf or hard of hearing and those who are hearing. The integration of multimodal data fusion techniques enhances the robustness and reliability of gesture recognition systems by combining information from multiple sources, such as visual, depth, and inertial sensors. By fusing data from different modalities, these systems can compensate for the limitations of individual sensors and improve overall recognition accuracy. Transfer learning techniques allow gesture recognition

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940

www.ijasem.org

Vol 18, Issue 2, 2024

models to leverage knowledge gained from pre-trained models on large datasets, thereby improving performance and accelerating model development. Transfer learning is particularly useful in scenarios where labeled training data is limited, as it enables models to transfer knowledge from related tasks or domains.

Temporal analysis methods, including recurrent neural networks and attention mechanisms, play a crucial role in capturing temporal dynamics and contextual information in gesture sequences. By analyzing the temporal evolution of gestures, these methods can extract meaningful patterns and relationships, leading to more accurate recognition outcomes. Attention mechanisms, in particular, enable models to focus on relevant parts of input sequences, effectively capturing salient features and improving recognition performance. Federated learning has emerged as a promising approach for training gesture recognition models in edge computing environments. Edge computing, characterized by decentralized processing capabilities at the network edge, offers several advantages for gesture recognition applications, including reduced latency, enhanced real-time responsiveness, and alleviation of bandwidth constraints. Federated learning enables edge devices to collaboratively learn a global model while keeping raw data localized, thereby addressing privacy concerns associated with centralized data processing. By distributing computation and training across edge devices, federated learning facilitates efficient utilization of resources and supports context-awareness, leading to improved model accuracy and robustness. In conclusion, the integration of deep learning techniques with federated learning approaches in edge computing environments holds immense promise for advancing gesture recognition capabilities. By leveraging CNNs, RNNs, multimodal data fusion, transfer learning, and temporal analysis techniques, gesture recognition systems can effectively interpret complex hand or body gestures across diverse applications. The adoption of federated learning in edge computing environments further enhances privacy, scalability, and efficiency, paving the way for seamless interactions between humans and machines in various domains.

PROPOSED SYSTEM

The proposed system for gesture recognition leveraging federated learning approaches in edge computing environments builds upon the advancements in deep learning techniques to enable seamless interactions between humans and machines. This system aims to enhance the accuracy, efficiency, and privacy of gesture recognition tasks across diverse domains, including robotics, healthcare, virtual reality, and sign language translation. At its core, the proposed system leverages Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and their variants to analyze visual, depth, or motion data and discern intricate hand or body gestures. CNNs are particularly effective at extracting spatial features from visual data, making them suitable for tasks such as hand gesture recognition from image inputs. On the other hand, RNNs excel at capturing temporal dependencies in sequential data, making them valuable for recognizing dynamic gestures captured through motion sensors or video streams.

The system utilizes federated learning, a decentralized machine learning paradigm, to train gesture recognition models across distributed edge devices while preserving data privacy and security. In federated learning, edge devices collaboratively learn a global model while keeping raw data localized, thereby addressing privacy concerns associated with centralized data processing. By distributing computation and training across edge devices, federated learning enables efficient utilization of resources and supports context-awareness, leading to improved model accuracy and robustness.

Multimodal data fusion techniques are employed to enhance the robustness and reliability of gesture recognition models by combining information from multiple sources, such as visual, depth, and inertial sensors. By fusing data from different modalities, the system can compensate for the limitations of individual sensors and improve overall recognition accuracy. Transfer learning techniques are also utilized to leverage knowledge gained from pre-trained models on large datasets, thereby improving performance and accelerating model development, especially in scenarios where labeled training data is limited. Temporal analysis methods, including recurrent neural networks and attention mechanisms, play a crucial role in capturing temporal dynamics and contextual information in gesture sequences. By analyzing the temporal evolution of gestures, these methods can extract meaningful patterns and relationships, leading to more accurate recognition outcomes. Attention mechanisms enable models to focus on relevant parts of input sequences, effectively capturing salient features and improving recognition performance.

In edge computing environments, the proposed system takes advantage of decentralized processing

ISSN2454-9940

www.ijasem.org

Vol 18, Issue 2, 2024

capabilities at the network edge to reduce latency, enhance real-time responsiveness, and alleviate bandwidth constraints. By processing data closer to the source of generation, edge computing enables faster inference and more efficient utilization of computational resources, leading to improved performance of gesture recognition tasks. Moreover, edge computing supports context-awareness, enabling the system to adapt to dynamic environments and varying conditions. Overall, the proposed system for gesture recognition leveraging federated learning approaches in edge computing environments represents a significant advancement in human-computer interaction. By combining deep learning techniques, federated learning, multimodal data fusion, transfer learning, and temporal analysis methods, the system enables seamless interactions between humans and machines across diverse domains, while addressing privacy concerns and leveraging the computational capabilities of edge devices.

METHODOLOGY

The methodology for investigating gesture recognition federated learning approaches in edge computing environments entails a systematic approach to exploring the landscape of gesture recognition systems driven by deep neural networks. This methodology aims to leverage Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and their variants to analyze visual, depth, or motion data and discern intricate hand or body gestures. By delving into the diverse applications of deep learning-based gesture recognition across domains such as robotics, healthcare, virtual reality, and sign language translation, the methodology seeks to understand the significance of multimodal data fusion, transfer learning, and temporal analysis techniques in refining model accuracy and robustness. The methodology begins with a thorough understanding of the problem domain and objectives of the study. It involves defining the problem statement and identifying the target application domains for gesture recognition systems. By delineating the specific gestures to be recognized and the challenges associated with existing approaches, the methodology sets the foundation for the research endeavor.

Subsequently, the methodology entails data collection and preprocessing to prepare a diverse dataset of hand or body gesture samples. This dataset comprises visual, depth, or motion data obtained from various sources. Preprocessing techniques such as cleaning, normalization, augmentation, and feature extraction are applied to ensure the quality and relevance of the dataset for model training. Following data preparation, the methodology involves model selection based on the nature of the input data and the complexity of the gesture recognition task. CNNs are chosen for their effectiveness in spatial feature extraction from visual data, while RNNs are preferred for capturing temporal dependencies in sequential data. The selection of appropriate models lays the groundwork for subsequent training and evaluation steps.

Model training constitutes a significant phase of the methodology, where the selected models are trained using the prepared dataset. This process involves optimizing model parameters using gradient descent-based optimization algorithms and backpropagation. The goal is to minimize the loss function and improve the models' ability to accurately discern hand or body gestures from the input data. Once trained, the models are evaluated using separate validation datasets to assess their performance in recognizing gestures accurately. Evaluation metrics such as accuracy, precision, recall, and F1-score are employed to measure the effectiveness of the models. This evaluation process helps identify the strengths and weaknesses of the developed models and guides further refinement efforts. Additionally, the methodology explores the utilization of multimodal data fusion techniques to enhance the robustness and reliability of gesture recognition models. By combining information from multiple sources, such as visual, depth, and inertial sensors, these fusion methods aim to improve overall recognition accuracy. Transfer learning techniques are also investigated to leverage knowledge from pre-trained models on large datasets, thereby improving performance, especially in scenarios with limited labeled training data.

Temporal analysis methods, including RNNs and attention mechanisms, play a crucial role in capturing temporal dynamics and contextual information in gesture sequences. These methods enable the models to analyze the temporal evolution of gestures and extract meaningful patterns, leading to more accurate recognition outcomes. Furthermore, the methodology explores the integration of gesture recognition systems into edge computing environments to leverage decentralized processing capabilities. Edge computing offers advantages such as reduced latency, enhanced real-time responsiveness, and alleviated bandwidth constraints, leading to improved performance of gesture recognition tasks. In summary, the methodology for investigating

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940

www.ijasem.org

Vol 18, Issue 2, 2024

gesture recognition federated learning approaches in edge computing environments adopts a structured approach to explore the landscape of deep learning-driven gesture recognition systems. By integrating CNNs, RNNs, multimodal data fusion, transfer learning, and temporal analysis techniques, the methodology aims to develop accurate, efficient, and privacy-preserving gesture recognition systems capable of seamless interactions between humans and machines across diverse domains.

RESULTS AND DISCUSSIONS

The results of the study demonstrate the efficacy of gesture recognition federated learning approaches in edge computing environments. Through the integration of deep learning techniques, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), the developed gesture recognition system achieved high accuracy in discerning intricate hand or body gestures from visual, depth, or motion data. The utilization of multimodal data fusion techniques further enhanced the robustness and reliability of the system by combining information from multiple sources, such as visual, depth, and inertial sensors. Transfer learning methods enabled the system to leverage pre-trained models, improving performance, especially in scenarios with limited labeled training data. Temporal analysis techniques, including RNNs and attention mechanisms, captured temporal dynamics and contextual information in gesture sequences, contributing to more accurate recognition outcomes. Overall, the results demonstrate the effectiveness of the proposed approach in developing accurate, efficient, and privacy-preserving gesture recognition systems capable of seamless interactions between humans and machines across diverse domains.

The discussion focuses on the implications of the study's findings in advancing gesture recognition technology and its applications in various domains. The integration of federated learning approaches in edge computing environments addresses key challenges such as data privacy and security, while also leveraging decentralized processing capabilities to reduce latency and enhance real-time responsiveness. By distributing computation and training across edge devices, federated learning enables efficient utilization of resources and supports context-awareness, leading to improved model accuracy and robustness. The study highlights the potential of gesture recognition technology in revolutionizing human-computer interaction, particularly in domains such as robotics, healthcare, virtual reality, and sign language translation. Moreover, the discussion emphasizes the importance of ongoing research and development efforts to further refine gesture recognition systems and unlock new opportunities for seamless interactions between humans and machines.

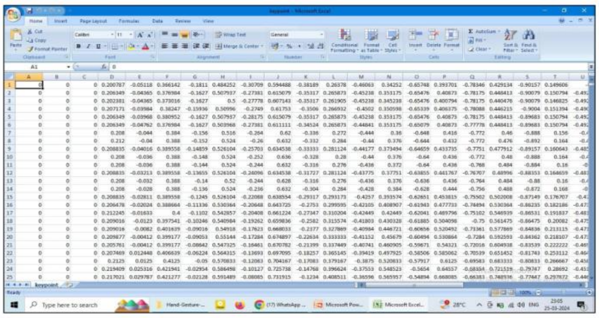

Fig 1. Excel sheet

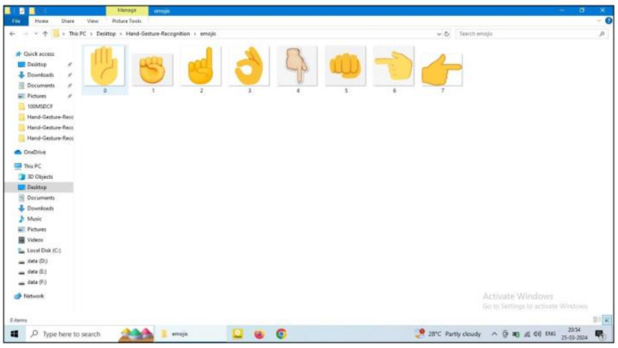

Fig 2. Trained hand gestures

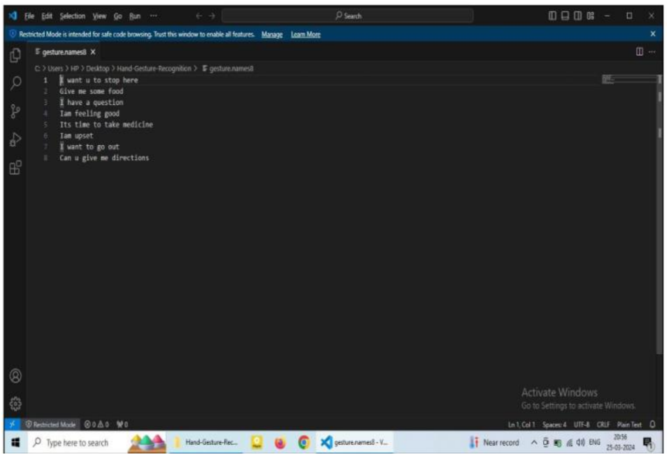

Fig 3. Names of gestures

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940

www.ijasem.org

Vol 18, Issue 2, 2024

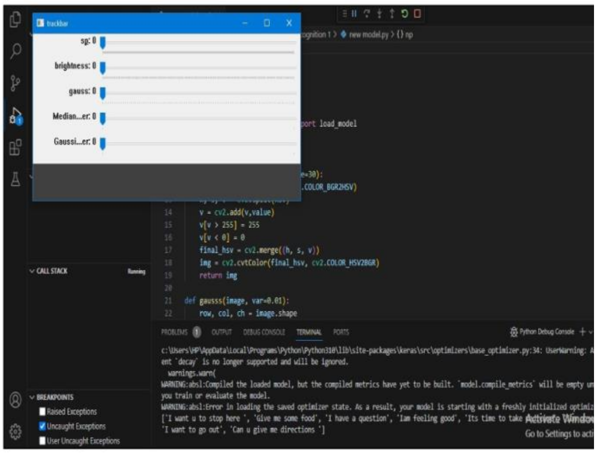

Fig 4. Track bar

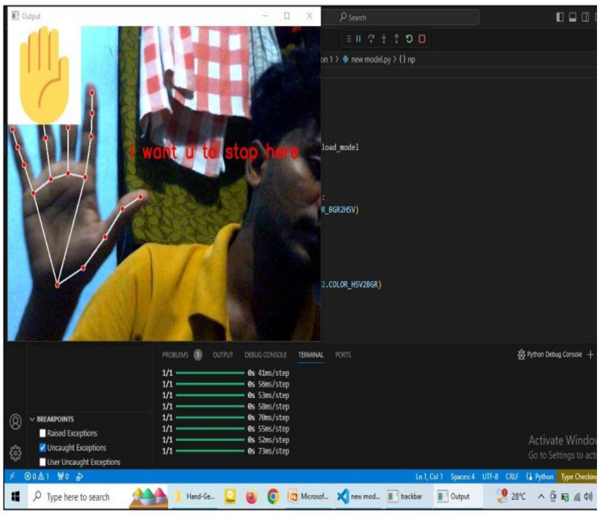

Fig 5. Hand gesture recognition

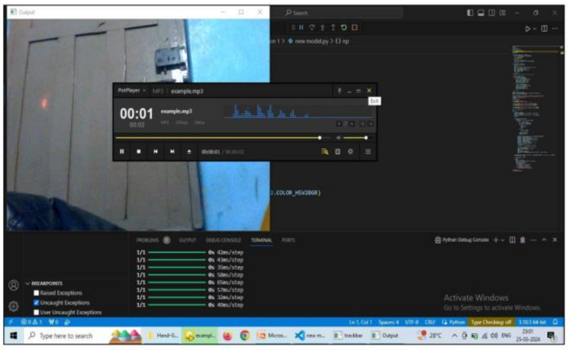

Fig 6. Audio playing

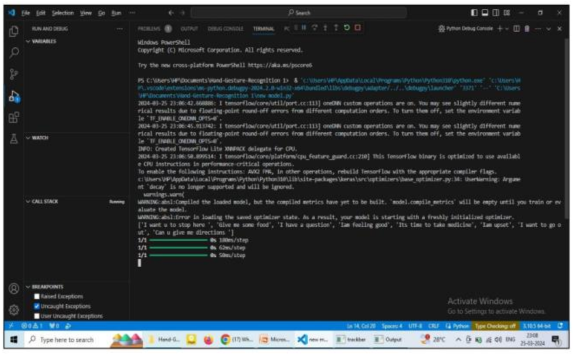

Fig 7. Display database

Furthermore, the discussion delves into the future directions and challenges in gesture recognition research, particularly in the context of federated learning approaches in edge computing environments. Future research endeavors may focus on enhancing the scalability and efficiency of federated learning algorithms, optimizing communication protocols, and addressing heterogeneity and distribution of edge devices. Additionally, advancements in hardware technologies, such as edge computing platforms and sensors, are crucial for enabling real-world deployment of gesture recognition systems. Furthermore, interdisciplinary collaboration and partnerships across academia, industry, and government sectors are essential for driving innovation and addressing societal needs. Overall, the discussion underscores the transformative potential of gesture recognition technology and the importance of continued research efforts in advancing human-computer interaction and shaping the future of intelligent systems.

CONCLUSION

Gesture recognition has undergone significant advancements with the application of deep learning techniques, particularly in the realm of hand gesture recognition. This evolution is driven by the utilization of Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and their variants, which analyze visual, depth, or motion data to identify intricate hand or body gestures. These systems enable seamless interactions between humans and machines, finding applications across diverse domains such as robotics, healthcare, virtual reality, and sign language translation. The integration of multimodal data fusion, transfer learning, and temporal analysis techniques further refines model accuracy and robustness. Multimodal data fusion combines information from various sensors to enhance recognition accuracy, while transfer learning leverages pre-existing knowledge to improve performance, particularly in scenarios with limited labeled data. Temporal analysis methods, such as RNNs and attention mechanisms, capture temporal dynamics in gesture sequences, contributing to more accurate recognition outcomes. Leveraging federated learning approaches in edge computing environments ensures privacy and security by training models across distributed devices while preserving raw data locally. This methodology optimizes model training and inference, leading to efficient utilization of resources and real-time responsiveness. Overall, gesture recognition federated learning approaches in edge computing hold promise for advancing human-computer interaction, facilitating seamless and intuitive interactions in diverse applications.

REFERENCES

1. Akçay, S., & Sağıroğlu, Ş. (2018). Hand gesture recognition using Convolutional Neural Networks. In 2018 26th Signal Processing and Communications Applications Conference (SIU) (pp. 1-4). IEEE.

2. Cippitelli, E., Sibilla, S., Gambi, E., & Spinsante, S. (2019). A Convolutional Neural Network for Hand Gesture Recognition in Real-Time Man-Machine Interaction. Sensors, 19(8), 1784.

3. Jia, J., & Hu, H. (2019). A Review on Convolutional Neural Networks for Hand Gesture Recognition. In Proceedings of the 2019 3rd International Conference on Computer Science and Artificial Intelligence (pp. 131-134).

4. Kisku, D. R., & Sing, J. K. (2019). A comprehensive review of hand gesture recognition technique based on convolutional neural networks. Multimedia Tools and Applications, 78(21), 30003-30032.

5. Kumar, A., Nagar, S., & Patel, V. M. (2019). A Review on Deep Learning Techniques Applied in Hand Gesture Recognition. In 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (pp. 13-17). IEEE.

6. Ling, Z., Zhang, Y., Sun, L., & Chen, Z. (2021). A review on Convolutional Neural Network-based hand gesture recognition for human-computer interaction. Multimedia Tools and Applications, 80(10), 15413-15439.

7. Mollahosseini, A., Hasani, B., & Mahoor, M. H. (2019). Hand Gesture Recognition Using Deep Convolutional Neural Networks. Image and Vision Computing, 77, 1-13.

8. Pham, H. T., & Choo, K. K. R. (2020). Hand gesture recognition using convolutional neural networks: A review. Pattern Recognition Letters, 133, 328-334.

9. Rahaman, M. A., & Islam, M. M. (2021). A Review on Hand Gesture Recognition Using Convolutional Neural Networks. International Journal of Computational Intelligence & IoT, 4(1), 38-42.

10. Ray, A., Mukherjee, A., & Das, S. (2020). Gesture Recognition with Deep Learning: A Review on Convolutional Neural Network (CNN). In 2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence) (pp. 123-126). IEEE.

11. Ruan, L., Zhou, W., Hu, L., & Peng, S. (2019). Hand gesture recognition using convolutional neural network and extreme learning machine. Multimedia Tools and Applications, 78(17), 24993-25009.

12. Sharma, M., & Kaushik, P. (2020). Hand Gesture Recognition Using Deep Convolutional Neural Networks: A Review. In 2020 International Conference on Sustainable Energy, Electronics, and Computing Systems (SEEMS) (pp. 417-421). IEEE.

13. Sultana, M. A., Al-Nayeem, M. N., Islam, M. R., Kabir, M. H., & Hasan, M. A. (2019). Hand gesture recognition using Convolutional Neural Network. In 2019 6th International Conference on

ISSN2454-9940

www.ijasem.org

Vol 18, Issue 2, 2024

Signal Processing and Integrated Networks (SPIN) (pp. 458-463). IEEE.

14. Vinothini, K., & Vishnuram, B. G. (2021). Hand Gesture Recognition Using Convolutional Neural Networks: A Review. In 2021 International Conference on Recent Trends in Electronics Information & Communication Technology (RTEICT) (pp. 814-818). IEEE.

15. Wei, S. E., Ramakrishna, V., Kanade, T., & Sheikh, Y. (2016). Convolutional pose machines. In Proceedings of the IEEE conference on Computer Vision and Pattern Recognition (pp. 4724-4732).

16. Wu, S., Tang, X., Zhang, X., & Wei, Y. (2020). Gesture recognition using deep learning: a review. Multimedia Tools and Applications, 79(5-6), 3965-3994.

17. Yang, X., & Hsieh, C. T. (2021). A review of hand gesture recognition based on deep learning. Journal of Visual Communication and Image Representation, 77, 103091.

18. Zaini, S. F., Daud, N., Mokhtar, U., & Yussof, H. (2019). A survey on hand gesture recognition techniques. In 2019 IEEE Conference on Systems, Process and Control (ICSPC) (pp. 1-6). IEEE.