

Appendix A

List of Publications

A.1 Journal Papers

1. **Shashank Kumar Singh**, Amrita Chaturvedi: A reliable and efficient machine learning pipeline for American sign language gesture recognition using EMG sensors. In: *Multimedia Tools and Applications*, 82, 23833–23871 (Springer Nature) (2023) (Published) (**SCI/SCIE, IF: 3.00**)
2. **Shashank Kumar Singh**, Amrita Chaturvedi: Leveraging deep feature learning for wearable sensors based handwritten character recognition. In: *Biomedical Signal Processing and Control* (Elsevier), Vol. 80, Part 1, 104198, (2023) (Published) (**SCI/SCIE, IF: 4.9**)
3. **Shashank Kumar Singh**, Amrita Chaturvedi: "An efficient multi-modal sensors feature fusion approach for handwritten characters recognition using Shapley values and deep autoencoder." **Engineering Applications of Artificial Intelligence** 138 (2024): 109225. (Elsevier)(Published) (**SCI/SCIE, IF: 7.5**)
4. **Shashank Kumar Singh**, Amrita Chaturvedi: "A Cooperative game theory-based feature selection for efficient hand grasp classification using minimal

number of sEMG signals.” **ACM Transactions on Computing for Health-care** 6.1 (2025): 1-22. (**SCI/SCIE/ESCI**) (Published)

5. **Shashank Kumar Singh**, Amrita Chaturvedi, Ruhi Asitkumar Joshi, and Shruti Sharma: ”Improving Electromyography Signals Based Handwritten Character Recognition through Sensor Fusion and Meta-Heuristic Optimization.” In: **Computers and Electrical Engineering**,, 2024 (Elsevier)(Under Review) (**SCI/SCIE, IF: 4**)

A.2 Conference Papers

1. **Shashank Kumar Singh**, Amrita Chaturvedi, Alok Prakash: Applying Extreme Gradient Boosting for Surface EMG based Sign Language recognition. In: International Conference on Machine Learning and Big Data Analytics (ICMLBDA), Indian Institute of Technology, Patna, India, Lecture Notes in Networks and Systems, vol 256., SPRINGER AISC Series, pp 175 - 185. (March 2021) (**Published**)
2. **Shashank Kumar Singh**, Amrita Chaturvedi: Applying Machine Learning for American Sign Language Recognition: A brief survey. In: The 4th International Conference on Communication and Intelligent Systems (ICCIS 2022) (Springer), NIT Delhi, India, Lecture Notes in Networks and Systems (LNNS), Springer, Vol 689, pp 297-309. (December 2022) (**Published**)
3. **Shashank Kumar Singh**, Amrita Chaturvedi: ”Leveraging Handwriting Dynamics, Explainable AI and Machine Learning for Alzheimer Prediction.” International Conference on Computational Intelligence in Communications and Business Analytics. Cham: Springer Nature Switzerland, 2024. (**Published**)
4. **Shashank Kumar Singh**, Amrita Chaturvedi: ”Machine Learning for Sensor-Based Handwritten Character Recognition: A Brief Survey.” International

Conference on Distributed Computing and Intelligent Technology. Cham:
Springer Nature Switzerland, 2024. **(Published)**

A.3 Patents

1. **Shashank Kumar Singh**, Amrita Chaturvedi, Title for the invention: "Method and System for Handwritten Character Recognition Using Multi-Modal Sensor Fusion and Enhanced Salp Swarm Algorithm" (Indian Patent) (**Application No: 202411082614**)
2. **Shashank Kumar Singh**, Amrita Chaturvedi, Title of the invention: "Method for Efficient Hand Grasp Classification Using Minimal sEMG Sensors and Cooperative Game Theory" (Indian Patent) (**Application No: 202411097957**)

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- [5] S. K. Singh and A. Chaturvedi, “A reliable and efficient machine learning pipeline for american sign language gesture recognition using emg sensors,” *Multimedia Tools and Applications*, 2023, v. 82, n. 15, pp. 23 833–23 871.
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