International Journal of Research and Development in Applied Science and Engineering (IJRDASE)
ISSN: 2454-6844

A Sustainable Wireless Sensor Network Framework for Long-Term Patient Monitoring and Healthcare Applications

Brijesh Kumar Yadav, Dr. Abhishek Srivastava
Department of Electronics and Communication Engineering
Institute of Engineering and Technology, Dr. RML Awadh University, Ayodhya, U.P., India
erbrijesh2207@gmail.com. abhishek200959@gmail.com

Abstract: This research presents an IoT-enabled healthcare monitoring framework that integrates Wireless Sensor Networks (WSNs), cloud computing, and the ThingSpeak IoT platform to provide reliable and continuous remote patient monitoring. Biomedical sensor data, including vital physiological parameters, are continuously acquired through IoT-enabled sensing devices and securely transmitted to cloud servers using reliable communication protocols. The collected data are stored, visualized, and analyzed within the MATLAB environment, enabling real-time health assessment, remote patient supervision, and intelligent clinical decision support. To enhance communication efficiency, three nature-inspired optimization algorithms—Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Grey Wolf Optimization (GWO)—are employed for congestion-aware routing and intelligent path selection. These optimization techniques identify the most efficient communication routes by considering network conditions, transmission delay, residual energy, and routing fitness, thereby reducing network congestion, minimizing packet loss, and improving overall data transmission reliability. Furthermore, the proposed framework supports energy-efficient routing, prolongs the operational lifetime of WSN nodes, and ensures timely delivery of critical healthcare data. The integration of IoT, cloud computing, MATLAB analytics, and intelligent optimization techniques provides a scalable, robust, and cost-effective solution for next-generation remote healthcare monitoring systems, improving both network performance and the quality of patient care.

Keywords: IoT, IMU, WSN, ACO, PSO

1. Introduction:

Human gait recognition has emerged as a significant research area due to its wide range of applications in healthcare, rehabilitation, sports science, elderly care, and assistive robotics. Gait velocity, commonly referred to as self-selected walking speed, is a simple, reliable, and clinically relevant parameter for assessing an individual's functional mobility and gait biomechanics. It provides valuable insights into physical health, mobility impairments, and disease progression, making it an important indicator for early diagnosis and rehabilitation planning. Recent advances in wearable sensing technologies and machine learning have enabled accurate and automated gait analysis using compact, low-cost, and portable devices. Conventionally, gait analysis has been performed using force plates, motion capture systems, and Human Activity Recognition (HAR) frameworks. HAR systems are broadly classified into vision-based and sensor-based approaches. Vision-based methods, which rely on cameras and video recordings, can provide detailed motion information but often suffer from limitations such as high computational complexity, privacy concerns, sensitivity to environmental conditions, and large data storage requirements. In contrast, wearable sensor-based systems offer a more practical and cost-effective solution for continuous gait monitoring in both clinical and real-world environments. Sensors such as accelerometers, gyroscopes, magnetometers, inertial measurement units (IMUs), electromyography (EMG), goniometers (GON), and IoT-enabled wearable devices have been extensively utilized to capture human motion with high accuracy. Among these, IMU sensors are particularly popular because of their compact size, low power consumption, lightweight design, and ability to measure three-dimensional acceleration and angular velocity.

The collected wearable sensor data are processed to extract temporal, statistical, and frequency-domain features that characterize different walking patterns. These features are subsequently analyzed using machine learning algorithms to classify gait velocity and recognize various human activities. Machine learning-based gait classification has demonstrated promising results in applications including rehabilitation robotics, assistive devices, gait abnormality detection, fall-risk assessment, neurological disorder diagnosis, and elderly healthcare. By learning discriminative patterns from sensor data, machine learning models can provide accurate and reliable gait recognition while reducing the need for expensive laboratory-based equipment.

This study proposes a machine learning-based framework to investigate the impact of wearable IMU and goniometer (GON) sensor fusion, along with single- and multi-sensor configurations, on gait speed classification performance. Wearable sensor signals are preprocessed, relevant features are extracted, and multiple machine learning algorithms are employed to recognize different gait patterns based on temporal gait characteristics. The proposed framework systematically evaluates the effectiveness of various classifiers in identifying gait speed while examining the benefits of multimodal sensor fusion for improving classification accuracy, robustness, and reliability. The findings of this study contribute to the development of intelligent wearable healthcare systems capable of real-time gait monitoring and personalized rehabilitation support.

2. Related Work:

Several researchers have investigated wearable sensor-based gait analysis using machine learning and deep learning techniques to improve gait recognition, walking speed estimation, and disease diagnosis. Bhakta et al. proposed a machine learning framework for continuous walking speed estimation using embedded IMU sensors integrated into knee and ankle prostheses. Their subject-independent model demonstrated high prediction accuracy, achieving a Root Mean Square Error (RMSE) of 0.070 ± 0.007 m/s, highlighting the effectiveness of wearable IMU sensors for real-time gait speed estimation.

Camargo et al. conducted a comprehensive study on sensor selection and placement for gait classification using wearable sensor fusion. Their proposed system combined Inertial Measurement Unit (IMU), goniometer (GON), and electromyography (EMG) sensors to estimate ground-level walking speed. The fusion-based framework achieved an impressive 96% classification accuracy at a walking speed of 0.04 m/s, demonstrating that multimodal sensor fusion significantly enhances gait recognition performance compared to individual sensors.

Several studies have focused on gait analysis for neurological disorder diagnosis. Nasrabadi et al. developed an IMU-based human activity recognition framework for the telerehabilitation of Parkinson's disease patients. Their model achieved a sensitivity exceeding 87%, while IMU sensors positioned on the thigh alone provided a 93% recall, indicating that appropriate sensor placement plays a crucial role in improving recognition performance. Similarly, Ferreira et al. investigated Parkinson's disease stage classification using machine learning models trained on spatiotemporal gait parameters and reported a disease detection accuracy of 84.6%. In another related study, Trabassi et al. utilized IMU-derived gait features with Support Vector Machine (SVM) and Decision Tree (DT) classifiers, obtaining classification accuracies greater than 80%, further validating the effectiveness of wearable sensing technologies for neurological disease assessment.

Wearable sensor configuration has also been extensively explored. De Vos et al. employed six wearable IMU sensors to classify different neurodegenerative diseases and observed that the highest classification performance was achieved when all sensors were utilized simultaneously. However, they also reported that a single lumbar-mounted IMU sensor could provide comparable accuracy, making it an attractive option for practical wearable healthcare applications.

The influence of sensor placement on gait recognition has been examined by Dehzangi et al., who deployed five IMU sensors on the chest, waist, wrist, and knees of participants. Using deep learning techniques, their framework achieved 91% gait recognition accuracy, demonstrating the importance of optimal sensor positioning. In another study, the same authors applied a two-dimensional (2D) time-frequency transformation to gait signals collected from multiple wearable inertial sensors. Instantaneous frequencies extracted from the transformed signals were used as gait descriptors, resulting in an impressive recognition accuracy of 93.4%, confirming the discriminative capability of time-frequency features.

Walking pattern analysis across different age groups has also attracted considerable attention. Zhong et al. investigated gait characteristics in young and older adults using a smart bracelet equipped with accelerometer sensors. Their experimental results revealed that the Root Mean Square (RMS) acceleration measured at the right ankle increased proportionally with walking speed, demonstrating the effectiveness of wearable accelerometers in monitoring gait dynamics.

In activity recognition studies, Kececi et al. utilized an open-source dataset collected from wearable IMU sensors positioned on the thigh, shank, and foot to classify activities such as walking and running using machine learning algorithms. Their findings demonstrated that wearable IMU sensors can accurately distinguish between various locomotion activities under different movement conditions.

Vision-based human activity recognition has also shown promising performance. Genc et al. proposed a hybrid deep learning architecture combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to analyze video-based human activities, achieving a classification accuracy of 94.1%. Likewise, Kapoor et al. introduced a novel feature descriptor based on Finite Element Analysis (FEA) for video-based activity recognition. The extracted features were classified using Support Vector Machine (SVM) and Radial Basis Function (RBF) classifiers, resulting in an accuracy of 90.2%, demonstrating the effectiveness of handcrafted descriptors combined with machine learning techniques.

Beyond activity recognition, gait analysis has also been applied to biometric estimation. Ahad et al. proposed a wearable sensor-based framework for automatic gender and age estimation using gait dynamics. Their angle-embedded gait dynamic image representation, combined with deep learning, achieved a gender estimation error of 0.242 and a Mean Absolute Error (MAE) of 5.39 years for age estimation, illustrating the potential of gait-based biometric analysis in intelligent healthcare and security applications.

Overall, the literature demonstrates that wearable IMU sensors, sensor fusion techniques, and machine learning algorithms have substantially advanced human gait recognition. Appropriate sensor placement, multimodal sensing, and robust feature extraction methods consistently improve classification accuracy and reliability. These findings highlight the growing potential of intelligent wearable systems for healthcare monitoring, rehabilitation, neurological disease diagnosis, and personalized gait assessment.

International Journal of Research and Development in Applied Science and Engineering (IJRDASE)
ISSN: 2454-6844

3. Methodology:

ACO:

The Ant Colony Optimization (ACO) algorithm is a nature-inspired metaheuristic based on the foraging behavior of real ants, which communicate through pheromone trails to discover the shortest paths between their nest and food sources. In communication networks, ACO is widely employed to determine optimal routing paths by exploring multiple transmission routes and selecting the most efficient path for reliable data delivery. The primary objective is to identify the shortest and most efficient communication route while minimizing transmission delay, congestion, and overall routing cost.

In ACO, the communication network is represented as a graph where each node corresponds to a sensor or communication device, and each edge represents a possible transmission link between two nodes. Artificial ants traverse the graph to construct feasible routing paths from the source to the destination. During each iteration, an ant probabilistically selects the next node based on two important factors: the pheromone intensity deposited on the communication link and heuristic information such as distance, residual energy, or transmission quality. Nodes with higher pheromone concentration and better network conditions are assigned a higher probability of being selected, allowing the algorithm to balance exploration of new routes with exploitation of previously successful paths.

The optimization process is iterative, with multiple artificial ants simultaneously exploring different routing alternatives. Each ant constructs a complete communication path while ensuring that previously visited nodes are avoided whenever necessary, thereby preventing routing loops. After all ants complete their paths, the quality of each route is evaluated using a fitness function that may consider transmission delay, packet delivery ratio, hop count, energy consumption, and network congestion. The pheromone levels on high-quality paths are reinforced, whereas pheromone values on less efficient routes gradually evaporate. This pheromone update mechanism enables the colony to progressively converge toward the optimal routing solution while maintaining adaptability to dynamic network conditions.

Because of its distributed search capability, positive feedback mechanism, and robustness against network changes, ACO has become an effective optimization technique for Wireless Sensor Networks (WSNs), Internet of Things (IoT) systems, and mobile communication networks. The algorithm enhances routing efficiency by reducing packet loss, minimizing communication delay, balancing network traffic, and extending the operational lifetime of sensor nodes. These characteristics make ACO particularly suitable for congestion-aware routing and intelligent path selection in real-time healthcare monitoring and other IoT-enabled applications.

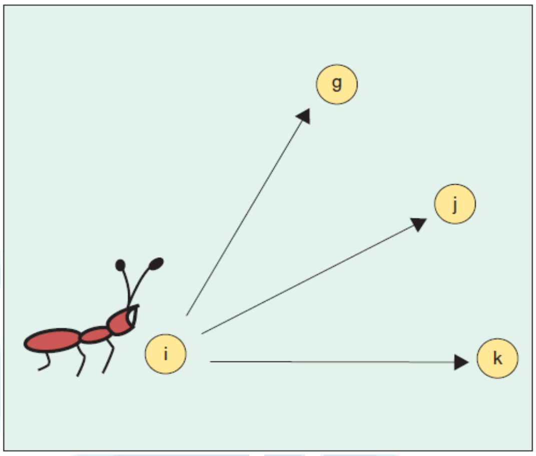

Fig 1: An ant in node i uses a stochastic technique to determine which node to visit next. If node j hasn't been visited yet, it can be chosen with a probability proportional to the pheromone connected to edge (i,j).

Proposed Work:

The MatLab program runs the algorithm to determine the best way to minimize congestion. The program utilizes algorithms for particle swarm optimization, ant colony optimization, and grey wolf optimization to determine the optimal path for healthcare data transmission with the least amount of congestion. The recommended method improves network load balancing and prevents congestion, which increases IoT web service throughput and performance. Based on three distinct optimization techniques, the algorithm finds optimal routing pathways and secondary paths by using the principle of intelligent solutions [20, 21, 22]. By identifying and selecting the best route, the algorithm presented here generates an intelligent solution of potential fittest pathways to convey data from source point to destination. The section that follows provides a step-by-step explanation of the suggested approach:

• Detection of different paths from source node to destination node by forwarding 'Request' packet.

• Backward bounces of 'Acknowledgement' packets from the destination to source node to update routing tables of the nodes that are passed through.

• Intelligent utilization of Information of the link quality estimate from table by collected information.

• Discovering the secondary ideal paths (source node to destination node) on the moments of data is exceeding queue limits in primary path (situation of congestion).

• Backward bounces from the destination node to source node via the new paths with respect to updates in routing tables for nodes involved in secondary ideal path.

• Broadcasting of the table of estimated link quality by collection of information of local secondary links.

The algorithm proposed in this work used three data tables for in the network's node for performing routing using ideal path selection as primary ad alternative secondary path:

1. Probabilistic data structure: This table is including the values of probability of neighbour nodes that may be selected in next hop on reaching towards the destination. It is including track information for directing the data packets towards destination. It also contains route information as set

International Journal of Research and Development in Applied Science and Engineering (IJRDASE)
ISSN: 2454-6844

of node id covered under a specific path. [23, 24, and 25]. In this manner this data structure is including following fields:
• Target-ID: It is representing the target node address.
• Next-hop-ID: It is containing next adjacent node address used for reaching the destination.
• State values field: estimated probabilities of neighboring nodes to be elected in next hop.
The probabilistic table describes for a node N containing R_N rows ($R_N = |S.N_N|$, ($S.N_N$ is set of nodes adjacent to the node N). C columns are representing total possible paths to reach the destination. For the $Pro_{L.T}$: probabilities of packets transmission through the link L. The following relation is followed for column entries as State values field tables for k^{th} device id. Hence, following relation is formulated in column of probability table:

$$\sum_{L\epsilon S.N_N} Pro_{L.T} = 1 \; \forall \, T \; \epsilon \; [1 \ldots C]$$

2. Delay data structure: This table is consisting of rate delay time value taken under passing data through the intermediate nodes. It contains N entries for each trip. The delay rates kept for M number search agents.
3. Link estimation table: This table is containing information of quality and strength of links. The values exploit the information to measure the levels of strength of links, taking account of delay of sending packets.

4. Result and Discussion:

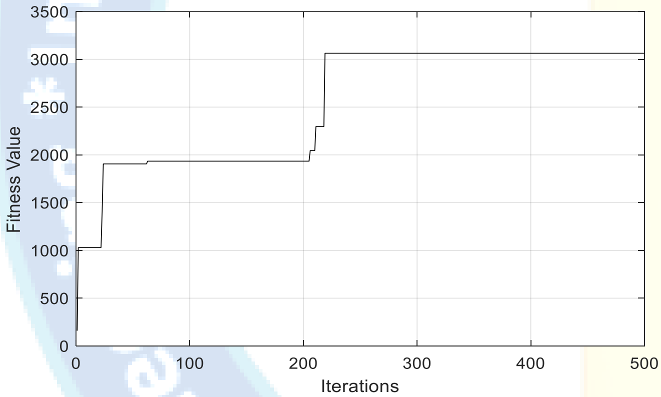

Fig 2: Fitness value convergence plot with respect to number of iterations

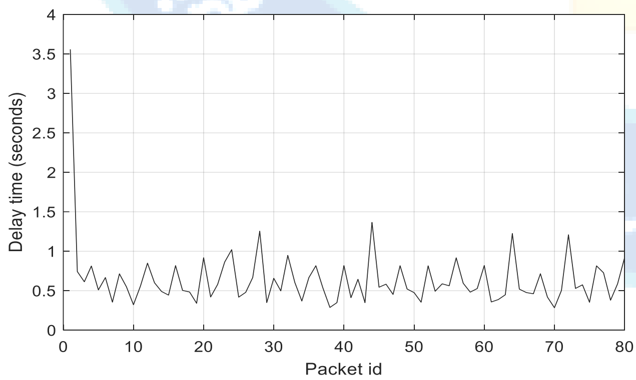

Fig 3: Delay time variation with respect to packet id

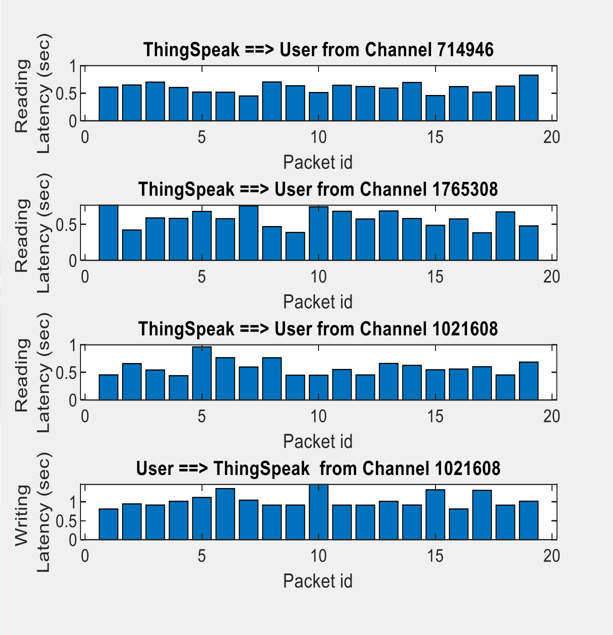

Fig 4: Reading and writing latency for user and ThingSpeak channel using PSO

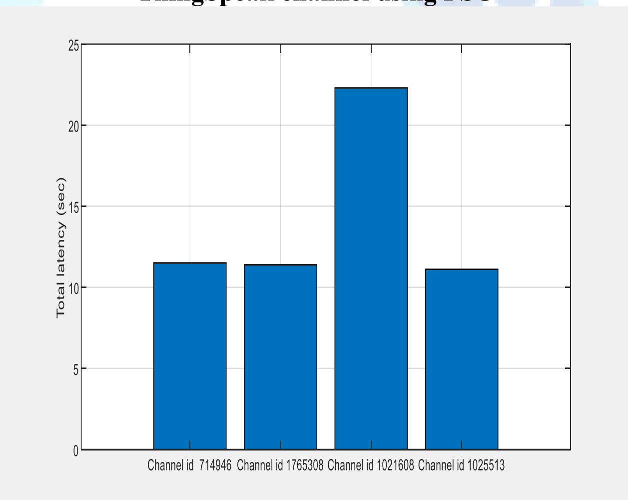

Fig 5: Total latency at different channel using PSO

Table 1: Comparative values of different optimization algorithm performance

	ACO
Iterations	219
Fitness Value	3026

Table 2: Comparative values of different optimization algorithm in terms of average delay and network set up time.

	ACO

Average Delay (sec)	0.60
Network Setup time (sec)	0.88

Table 3 Comparison of PSO, GWO and ACO performance in terms of total latency on reading and writing mode through different channels

	Total Latency (sec)	*ACO*
Reading mode	**ThingSpeak to user for channel 12397**	10.02
	ThingSpeak to user for channel 234684	19.67
	ThingSpeak to user for channel 1293177	20.08
	Total Reading Mode Latency (sec)	49.77
Write Mode	**User to ThingSpeak for channel 17504**	10.55
	Throughput (Kbps)	3025

5. Conclusion:

The research successfully demonstrates that integrating IoT technology with Wireless Sensor Networks provides an effective platform for continuous patient monitoring and remote healthcare management. The proposed framework enables real-time acquisition, cloud-based storage, visualization, and analysis of physiological information using the ThingSpeak platform and MATLAB environment. The integration of wearable sensors with cloud computing facilitates timely access to patient information, thereby improving clinical decision-making and supporting emergency healthcare services.

References

[1] M. Montero-Odasso, M. Schapira, E. R. Soriano, M. Varela, R. Kaplan, L.A. Camera, and L. M. Mayorga, "Gait velocity as a single predictor of adverse events in healthy seniors aged 75 years and older.", *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, vol. 60, no. 10, pp. 1304-1309, 2020. Available: https://academic.oup.com/biomedgerontology/article/60/10/13 04/553147

[2] K. Bhakta, J. Camargo, W. Compton, K. Herrin, and A. Young, "Evaluation of continuous walking speed determination algorithms and embedded sensors for a powered knee & ankle prosthesis," *IEEE Robotics and Automation Letters*, vol. 6, no. 3, pp. 4820–4826, 2021. doi: 10.1109/LRA.2021.3068711.

[3] J. Camargo, W. Flanagan, N. Csomay-Shanklin, B. Kanwar, and A. Young, "A Machine Learning Strategy for Locomotion Classification and Parameter Estimation Using Fusion of Wearable Sensors," *IEEE Transactions on Biomedical Engineering*, vol. 68, no. 5, pp. 1569–1578, 2021. doi: 10.1109/TBME.2021.3065809.

[4] A. M. Nasrabadi, A. R. Eslaminia, P. R. Bakhshayesh, M. Ejtehadi, L. Alibiglou, and S. Behzadipour, "A new scheme for the development of IMU-based activity recognition systems for telerehabilitation*," Medical Engineering & Physics*, vol. 108, 2022. doi: 10.1016/j.medengphy.2022.103876.

[5] M. I. A. S. N. Ferreira, F. A. Barbieri, V. C. Moreno, T. Penedo, and J. M. R. S. Tavares, "Machine learning models for Parkinson's disease detection and stage classification based on spatial-temporal gait parameters," *Gait Posture*, vol. 98, pp. 49–55, 2022. doi: 10.1016/j.gaitpost.2022.08.014.

[6] D. Trabassi, M. Serrao, T. Varrecchia, A. Ranavolo, G. Coppola, R. De Icco, and S. F. Castiglia, "Machine Learning Approach to Support the Detection of Parkinson's Disease in IMU-Based Gait Analysis," *Sensors*, vol. 22, no. 10, 2022. doi: 10.3390/s22103700.

[7] M. De Vos, J. Prince, T. Buchanan, J. J. FitzGerald, and C. A. Antoniades, "Discriminating progressive supranuclear palsy from Parkinson's disease using wearable technology and machine learning," *Gait Posture*, vol. 77, pp. 257–263, 2020. doi: 10.1016/j.gaitpost.2020.02.007.

[8] P. Panyakaew, N. Pornputtapong, and R. Bhidayasiri, "Using machine learning-based analytics of daily activities to identify modifiable risk factors for falling in Parkinson's disease," *Parkinsonism & Related Disorders*, vol. 82, pp. 77–83, 2021. doi: 10.1016/j.parkreldis.2020.11.014.

[9] E. Reznick, K. R. Embry, R. Neuman, E. Bolívar-Nieto, N. P. Fey, and R. D. Gregg, "Lower-limb kinematics and kinetics during continuously varying human locomotion," *Scientific Data*, vol. 8, no. 1, 2021. doi: 10.1038/s41597-021-01057-9.

[10] D. Jung, D. Nguyen, M. Park, J. Kim, and K.-R. Mun, "Multiple Classification of Gait Using Time-Frequency Representations and Deep Convolutional Neural Networks," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 4, 2020. doi: 10.1109/TNSRE.2020.2977049.

[11] O. Dehzangi and M. Taherisadr, "Human gait identification using two dimensional multi-resolution analysis," *Smart Health*, vol. 19, 2021. doi: 10.1016/j.smhl.2020.100167.

[12] R. Kapoor, O. Mishra, and M. M. Tripathi, "Human action recognition using descriptor based on selective finite element analysis," *Journal of Electrical Engineering*, vol. 70, no. 6, pp. 443–453, 2020. doi: 10.2478/jee-2019-0077.

[13] E. Genc, M. E. Yildirim, and Y. B. Salman, "Human activity recognition with fine-tuned CNN-LSTM," *Journal of Electrical Engineering*, vol. 75, no. 1, pp. 8–13, 2024. doi: 10.2478/jee-2024-0002

[14] O. Dehzangi, M. Taherisadr, and R. Changalvala, "IMU-Based Gait Recognition Using Convolutional Neural Networks and Multi-Sensor Fusion", *Sensors*, vol. 17, no. 12, pp. 2735, 2017. doi: 10.3390/s17122735.

ISSN: 2454-6844

[15] R. Zhong, P.-L. P. Rau, and X. Yan, "Gait Assessment of Younger and Older Adults with Portable Motion-Sensing Methods: A User Study", *Mobile Information Systems*, vol. 2019, no. 1, pp. 1093514, 2019. doi: 10.1155/2019/1093514.
[16] A. Kececi, A. ˘an Yildirak, K. Ozyazici, G. Ayluctarhan, O. Agbulut, and I. Zincir, "Implementation of machine learning algorithms for gait recognition", *Engineering Science and Technology, an International Journal*, vol. 23, no. 4, pp. 931- 937, 2020. doi: 10.1016/j.jestch.2020.01.005.
[17] M. A. R. Ahad, T. T. Ngo, A. D. Antar, M. Ahmed, T. Hossain, D. Muramatsu and, Y. Yagi, "Wearable sensor-based gait analysis for age and gender estimation", *Sensors (Switzerland)*, vol. 20, no. 8, 2020. doi: 10.3390/s20082424.
[18] J. Camargo, A. Ramanathan, W. Flanagan, and A. Young, "A comprehensive, open-source dataset of lower limb biomechanics in multiple conditions of stairs, ramps, and levelground ambulation and transitions," *Journal of Biomechanics*, vol. 119, 2021, doi: 10.1016/j.jbiomech.2021.110320.
[19] H. Kuduz and F. Kaçar, "A deep learning approach for human gait recognition from time-frequency analysis images of inertial measurement unit signal", *International Journal of Applied Methods in Electronics and Computers*, vol. 11, no. 3, pp. 165-173, 2023, doi: 10.58190/ijamec.2023.44.
[20] M. De Vos, J. Prince, T. Buchanan, J. J. FitzGerald, and C. A. Antoniades, "Discriminating progressive supranuclear palsy from Parkinson's disease using wearable technology and machine learning," *Gait Posture*, vol. 77, pp. 257–263, 2020. doi: 10.1016/j.gaitpost.2020.02.007
[21] G. A. Akpakwu, B. J. Silva, G. P. Hancke, and A. M. Abu-Mahfouz, "A survey on 5G networks for the Internet of Things: Communication technologies and challenges," IEEE Access, vol. 6, pp. 3619–3647, 2018.
[22] A. Aijaz and A. H. Aghvami, "Cognitive machine-to-machine communications for Internet-of-Things: A protocol stack perspective," IEEE Internet Things J., vol. 2, no. 2, pp. 103–112, Apr. 2015.
[23] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of Things: A survey on enabling technologies, protocols, and applications," IEEE Commun. Surveys Tuts., vol. 17, no. 4, pp. 2347–2376, 4th Quart., 2015.