Indonesian Journal of Electrical Engineering and Computer Science
Vol. 38, No. 1, April 2025, pp. 120~132
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v38.i1.pp120-132

Designing stair climbing wheelchairs with surface prediction using theoretical analysis and machine learning

Pharan Chawaphan, Dechrit Maneetham, Padma Nyoman Crisnapati
Department of Mechatronics Engineering, Faculty of Technical Education, Rajamangala University of Technology Thanyaburi, Pathum Thani, Thailand

Article Info

Article history:

Received Mar 26, 2024
Revised Oct 7, 2024
Accepted Oct 30, 2024

Keywords:

Machine learning prediction
Safety enhancement
Stair climbing
Urban accessibility
Wheelchair mobility

ABSTRACT

Urban settings present considerable obstacles for those use personal mobility wheelchairs, especially when it comes to manoeuvring stairs. The objective of this study is to improve the safety and ease of use of wheelchairs designed for ascending stairs. The study aims to tackle the significant issue of instability and limited ability to adjust to different types of terrain. This research employs a holistic methodology that combines theoretical dynamic analysis, hardware design and simulation, and field testing, in addition to advanced machine learning approaches for surface prediction. Theoretical models guarantee the stability of the wheelchair, while hardware simulations offer valuable insights into its structural integrity. The data obtained from inertial measurement unit (IMU) sensors during field tests is analysed and categorised using models like random forest and gradient boosting, which exhibit exceptional accuracy in forecasting movement circumstances. The results demonstrate that the implementation of these combined techniques greatly enhances the wheelchair's capacity to safely manoeuvre over urban barriers. The study finds that the suggested solutions show great potential for creating intelligent mobility aids, which might be used to improve accessibility for those with mobility limitations.

This is an open access article under the CC BY-SA license.

Corresponding Author:

Dechrit Maneetham
Department of Mechatronics Engineering, Faculty of Technical Education
Rajamangala University of Technology Thanyaburi
39 Moo 1 Rangsit-Nakhon Nayok Rd, Khlong Hok, Khlong Luang, Pathum Thani, Thailand
Email: dechrit_m@rmutt.ac.th

1. INTRODUCTION

In recent years the personal mobility wheelchair market witnessed notable expansion, attributed to factors such as population growth and technological advancements [1]. Power wheelchairs notably dominate a significant segment of the overall market [2]. Despite the considerable size of the electric wheelchair market, various challenges hinder their widespread adoption. Accessibility emerges as a primary concern, as infrastructure designs often overlook the specific needs of personal mobility devices (PMD) users, predominantly reliant on wheeled mobility [3]. Globally, accessibility issues persist, posing significant obstacles for wheelchair users. Safety represents another prominent issue, with surveys indicating that a considerable percentage of power wheelchair users have experienced physical accidents or expressed feelings of vulnerability during operation [4]. While assessing physical security is relatively straightforward, comprehending its psychological dimensions proves intricate. Consequently, amidst the increasing utilization of PMDs for urban mobility, enhancing accessibility and ensuring both physical and psychological safety emerge as imperative considerations [5].

The increasing utilisation of personal mobility devices (PMDs) in urban settings underscores notable difficulties pertaining to safety and ease of usage, particularly when encountering staircases. Although electric wheelchairs have made significant progress, the problem of mounting stairs still persists, limiting the mobility and self-sufficiency of users. Nevertheless, various research and commercial endeavors have been undertaken to address this challenge. Previous research has explored various mechanisms for stair climbing, including foot-based, wheel cluster-based, hybrid, and tracked systems. While these studies have provided foundational knowledge, each approach presents limitations in terms of stability, maneuverability, and adaptability to different urban terrains. Classification studies have identified four main categories of stair climbing methods for wheelchairs: foot-based, wheel cluster-based, hybrid, and tracked mechanisms [6]. Stair climbing techniques based on feet manipulation utilize mechanical features to ascend stairs [7]. Likewise, within a wheel cluster-based system, multiple wheels positioned across various axes form a planetary configuration along a singular axis. This arrangement enables smooth movement by wheel rotation, permitting ascent aided by rotation around a common axis. Two-wheel clusters maintain dynamic stability by using an inverted pendulum-like control method, whereas three-wheel or hex-wheel clusters prioritise mechanical strength [8]. Hybrid mechanisms are a broad category of techniques that integrate legs and wheels through the use of kinematic arrangements that guarantee the ability to roll as well as climb [9]. While some studies recommend rolling legs for ascent, others combine standard wheels with movable rolling legs for a similar level of usefulness [10]. Furthermore, alternative hybrid designs feature powered omnidirectional wheels within a four-bar connecting leg framework [10]. Researchers have also introduced innovative concepts such as variable shape wheels tailored for both stair traversal and regular movement [11]. Additionally, unconventional methods including user-operated levers activating swivel legs have been explored [12]. In contrast, tracked drive mechanisms are favored for their simpler design and control dynamics. Models integrating variable geometry tracked fins have been devised to adapt to varying terrains. Moreover, advancements include the development of stair climber wheelchairs capable of transitioning between conventional wheel-driven motion and track-based locomotion, facilitated by a kinematic switching mechanism [13]. Notably, certain stair-climbing wheelchairs exclusively rely on a tracked locomotion system. Beyond mechanical considerations, the control aspects of PMD significantly impact performance. These devices often employ a human-in-the-loop approach, blending autonomous functions with manual input. In some cases, control extends to interpreting brain signals for the operation of smart wheelchairs [7].

However, wheelchairs face challenges when encountering obstacles of varying sizes, particularly in urban environments, due to their fixed wheel arrangement. Wheel-leg hybrid SCWs may not have an issue with this, but these robots find it difficult to manoeuvre around obstacles since they require more degrees of freedom (DOF) in order to assure safe climbing. These difficulties are further compounded by the hybrid robot's overall length as shown in [14], exceeds that of a conventional wheelchair, complicating rotation in tight spaces. Additionally, the intricacies involved in movement planning hinder the timely overcoming of obstacles, as discussed in [15]. These robots can only move in one direction straight up when climbing stairs, this of course limits the space for the robots to move. The previous research highlighted the significant growth in the personal mobility wheelchair market in 2020, driven by factors such as population increase and technological advancements. However, despite the prevalence of power wheelchairs, accessibility issues persist due to infrastructure design limitations, hindering their widespread adoption. Safety concerns also pose significant challenges, with a notable percentage of users reporting physical accidents and feelings of vulnerability during use [16]. Existing stair-climbing mechanisms often fail to balance the requirements for stability, compactness, and adaptability in diverse urban environments. Furthermore, the challenge of predicting and responding to different surface conditions during stair climbing remains inadequately addressed. To address these challenges, the study leveraged data from inertial measurement units (IMU sensors) to help robots recognize the slope of stairs they encounter. In this research, pose recording was carried out using sensor data from an IMU based on terrain challenges. IMU sensor data was collected while riding a stair climbing wheelchair on various stair surfaces in a university environment. The task aimed to predict the type of stairs (slope, flat, steep) the robot would encounter based on sensor data, such as acceleration and speed. Based on the navigation dataset obtained from the IMU sensor, preliminary research was conducted on the SCW environmental classification. Several machine learning classification algorithms are applied and compared to obtain the best model. This research introduces an innovative design of a stair-climbing wheelchair that integrates theoretical dynamic analysis with machine learning-based surface prediction. This approach not only ensures the stability of the wheelchair across various terrains but also enhances its adaptability to different urban obstacles through real-time surface condition prediction.

Machine learning classification involves training models to categorize input data into predefined classes, with evaluation serving as a critical process for assessing model performance [17]. Models like logistic regression, k-nearest neighbors (KNN), support vector classification (SVC), decision trees, random forest, gradient boosting, and adaptive boosting are commonly employed for this purpose [18]–[22]. Assessment criteria like accuracy, precision, recall, F1-score, and AUC are utilized to gauge the performance of classifiers. Accuracy assesses the ratio of correctly classified instances, precision concentrates on the accuracy of positive predictions, recall underscores the model's capability to detect positive instances, and the F1-score offers a balanced assessment of performance across both classes. The AUC score evaluates a classifier's ability to discriminate between positive and negative instances across various threshold values [23]. Effective evaluation enables informed decisions regarding model selection and optimization, ensuring the suitability of classifiers for specific stairs being ascended using the wheelchair. Drawing from extant literature and technology, this study makes the following contributions: i) presenting a cutting-edge concept for a robotic wheelchair that can use both straight and diagonal navigation techniques to manoeuvre around a variety of urban obstacles, including stairs and ii) collecting navigation datasets for SCW and comparing the classifications of machine learning models. The following sections detail the development of a theoretical dynamic model, hardware design and simulation, field testing, and the application of machine learning for surface prediction. The study concludes with a discussion of the implications of our findings and potential future directions.

2. METHOD

2.1. Theoretical dynamic analysis model

The proposed development of an all-terrain wheelchair was initially carried out with a solid conceptual model using solid modeling software. The conceptual model is further modified by considering the dynamic stability of a tracked mechanism for an all-terrain wheelchair. An in-depth analysis was carried out by considering the following points: i) most importantly, the tracked mechanism not only helps in climbing stairs, but is also best suited for all different terrains; ii) the mechanism must maintain stability when climbing any slope; iii) climb stairs comfortably without the possibility of falling; and iv) this will help in transmissibility through different standards of stairs irrespective of their dimensions. In tracked mechanisms there are two main types, namely one-part tracked and two-part tracked. The double-section track mechanism is more suitable for climbing stairs without discomfort and takes more into account the stability of the system's center of gravity.

Adapting a double track mechanism: After thorough evaluation of different stair climbing mechanism concepts, it was found that the integration of a double track mechanism with a three-wheel belt drive system is a more stable and economical solution. The mechanism is shown as shown in the Figure 1. wheel 1 can be rotated in the center of wheel 2 or can be adjusted, according to the angle of inclination between the width of the tread and the rise of the stairs. The 3 wheels are able to rotate according to their center in the middle of the middle wheel or 2 wheels, also helping the system prepare itself safely when climbing hills and stairs. Because there is a requirement for the racket to be attached electrolytically to the end wheel connection, the need for which is to maintain the angle of inclination relative to the angle of inclination of the stairs or incline used by the wheelchair.

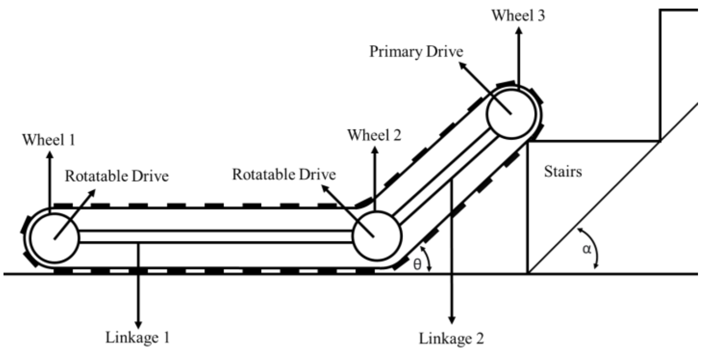
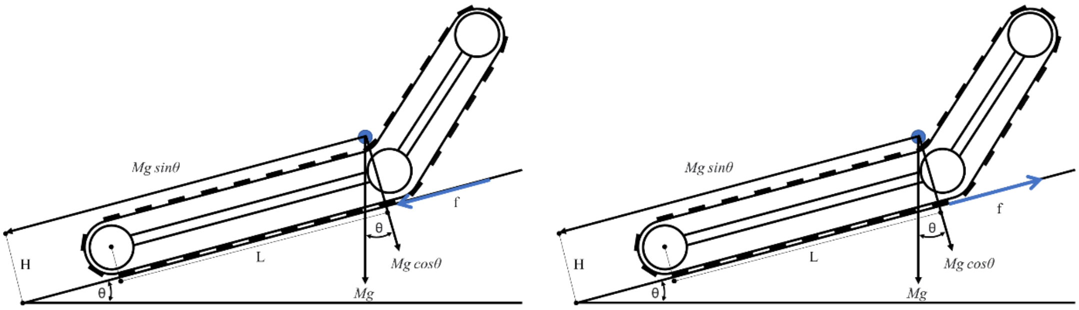


Figure 1. Stair climbing wheelchair mechanical design

Figure 2 shows the theoretical dynamic analysis model of the stair climbing wheelchair where Figure 2(a) presents the conditions when descending the slope, and Figure 2(b) ascending the slope. First, the center of mass of the entire conceptual model is searched theoretically using the averaging method for the moments generated by the centers of mass of the fragments that make up the whole complex system. The center of mass of the system is found first, then the center of mass of the human body is found in a sitting position, after that the center of mass of the system is found when the human is sitting. Since the mechanism involves rotation of the seat by 35 degrees, when climbing a slope or stairs, the center of mass of the system when the seat is rotated by an angle of 35 degrees is found. Basic analysis of dynamic theory is carried out based on the center of mass and its stability. Overturning becomes unavoidable if the center of mass balance fails. The following analysis was made.



(a) (b)

Figure 2. Theoretical dynamic analysis model (a) the conditions when descending the slope and (b) ascending the slope

As shown in the Figure 3, wheelchair while climbing the stairs or slope. The system moves upwards dynamically, the friction force acts in the upward direction on the plane because the track tries to push itself upwards by moving downwards (1) (if and only if the upward force is greater than mgsinθ then the system can move upwards) overturning occurs when the moment created by mgsinθ is greater than or equal to the moment created by mgcosθ or the normal reaction along the distance from the center of gravity to the center of the front wheel; (2) the equilibrium point is where overturning occurs, (3) and (4) for the maximum design angle θ=35 degrees. If (4) Then toppling can occur, cotθ=455/5502.127≠0.87 based on (5) and (6). Therefore, it is theoretically proven that the designed wheelchair will not topple when climbing stairs. Likewise, with wheelchairs when going down stairs.

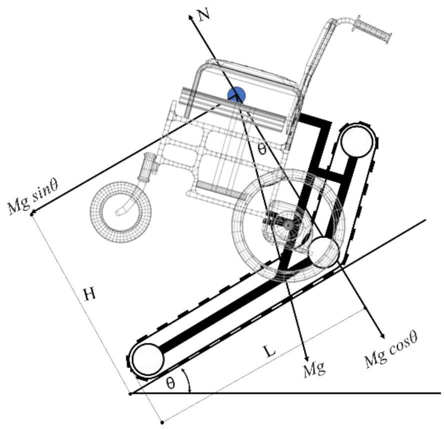


Figure 3. Theoretical dynamic analysis model with mounted wheelchair

$$f = mgsin\theta \tag{1}$$

$$mgsin\theta + 1 \geq mgcos\theta + 1 \tag{2}$$

$$mgsin\theta \times H = mgcos\theta \times L \tag{3}$$

$$cot\theta = H/L \tag{4}$$

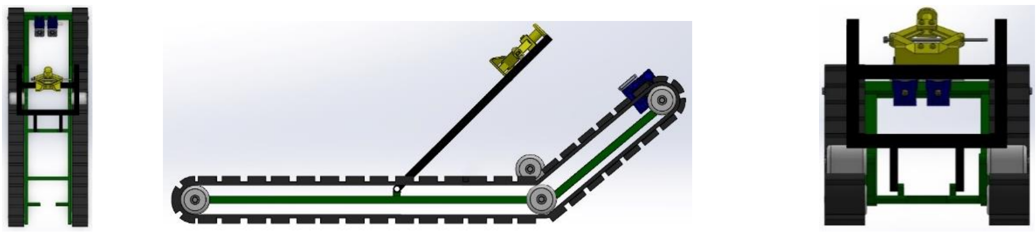
$$H = 455\,mm \tag{5}$$

$$L = (580 - 30) = 550\,mm \tag{6}$$

A conventional wheelchair design typically involves considering multiple factors, including loading conditions, terrain characteristics, accessibility for individuals with various disabilities, ergonomics, and other relevant aspects. Designing wheelchairs with specialized capabilities necessitates integrating factors such as mechanisms adapted for climbing terrain and considerations influencing the design of standard wheelchairs. Human dimensions, specifically those of the 85th percentile of Thai people based on global anthropometric data, play a significant role. These dimensions inform both the internal and external dimensions of the wheelchair. External dimensions are particularly influenced by safety-related and space-limiting factors. Safety considerations encompass factors like wheelchair stability, as represented by the equation $w\times mgcos\theta > h\times mgsin\theta$ only then the wheelchair can overcome the steep incline as shown in the first picture, if $L\times mgcos\theta > h\times mgsin\theta$ only, then the wheelchair can go transversely, downhill. where w represents width, h represents height, m represents mass, g represents gravity, and θ represents the angle of inclination. Moreover, space limitations, dictated by universally accepted standards for stair width, lift dimensions, and door width, are carefully accounted for in the wheelchair design process. Detailed evaluations of wheel width, diameter, and offset, along with chassis unit structural elements, are conducted to enhance user safety and comfort. The final design integrates all these factors to ensure a balance between functionality, safety, and ergonomic comfort.

2.2. Hardware design and simulation

Development of virtual 3D models: 3D solid models of each component are designed, taking into account the conceptual model and customized modifications. All components are assembled and checked for compatibility. The assembled model and it is explosive appearance are shown in the Figure 4. The software used for modeling is SOLIDWORKS 2019. Testing of this design was carried out by measuring simulations of Von Mises stress, deformation scale, resultant displacement, and factor of safety. As seen in Figure 4, a mechanical design rather than a wheelchair has been created. Sequentially, Figures 4(a)-4(c) are arranged from the top, left, and rear view.



(a) (b) (c)

Figure 4. 3D CAD design (a) top view, (b) side view, and (c) back view

2.2. Evaluation scenario

In addition to simulations, evaluation is also carried out by conducting field testing. There are three scenario conditions, where the scenario is seen in Figure 5. In the first scenario, the wheelchair is run on a fairly steep staircase as illustrated in Figure 5(a). The second scenario as shown in Figure 5(b) was tested on a flat slope with 10 slope degrees. While the third scenario as shown in Figure 5(c) is carried out on stairs with a large enough width and a slope that is not too steep. These three scenarios are then carried out twice, the first data taken will be a training dataset while the second data will be dataset testing.

2.3. Data collecting, preprocessing, and exploratory analysis

Data recording is also carried out during this testing process, while the stages of the process can be seen in Figure 6. Several measurement features are used in data recording such as gyroscope, accelerometer, magnetometer, gravity, linear velocity, and orientation. The raw data obtained is then processed into a form that is easier to understand and annotated or labeled. Annotations are carried out with six classes of wheelchair movement conditions when climbing or descending stairs, namely i) down_stairs; ii) up_stairs; iii) down_slope; iv) up_slope; v) down_largestair; vi) up_largestair. After that, the data is then saved into csv form and visualized using Python programming language on Google Colab. As the final stage of data collection and preparation, correlation matrix calculations of each feature are carried out.

(a) (b) (c)

Figure 5. Evaluation scenario (a) down and upstairs, (b) down and upslope, and (c) down and up large stair

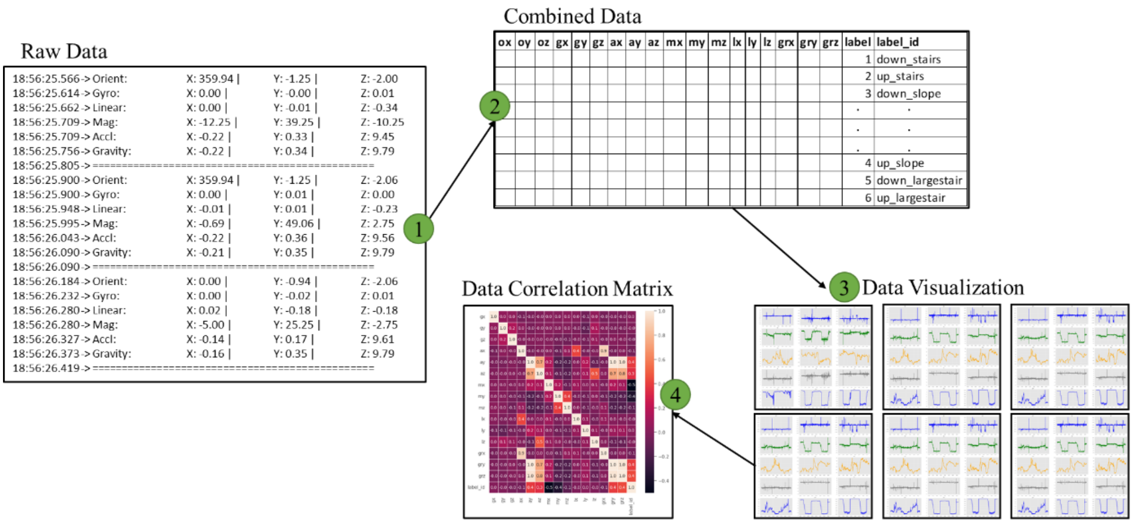


Figure 6. Data collecting and visualization phase

2.4. Machine learning flow and evaluation

The dataset that has been successfully collected is then divided into two, training and testing. In Figure 7, you can see the training dataset used to train models from each machine learning algorithm. Then from the model that has been obtained, tested using dataset testing. The results of this model are then validated and evaluated using accuracy, precision, recall, and F1 measurements. In addition, confusion matrix and ROC charts are used to visualize results rather than evaluations [24], [25].

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \tag{7}$$

$$Precision = \frac{True\ Positives}{True\ Positives + Flase\ Positives} \tag{8}$$

$$Recall = \frac{True\ Positives}{True\ Positives + Flase\ Negatives} \tag{9}$$

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{10}$$

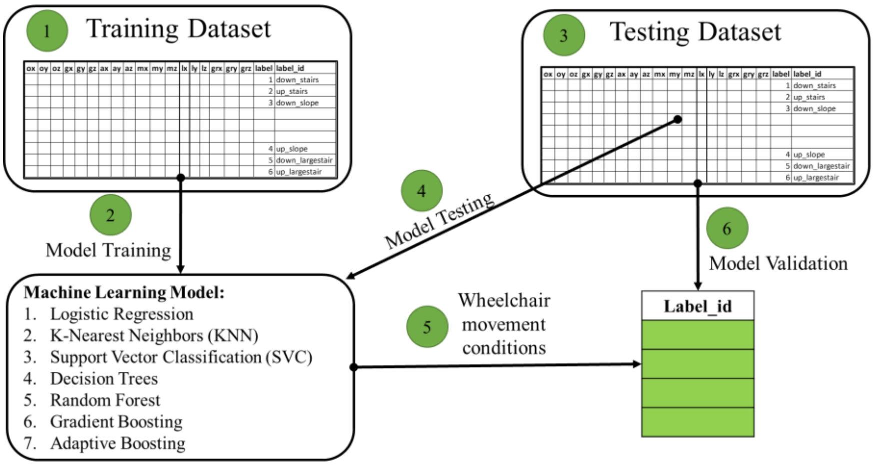


Figure 7. Conceptual research design for classification

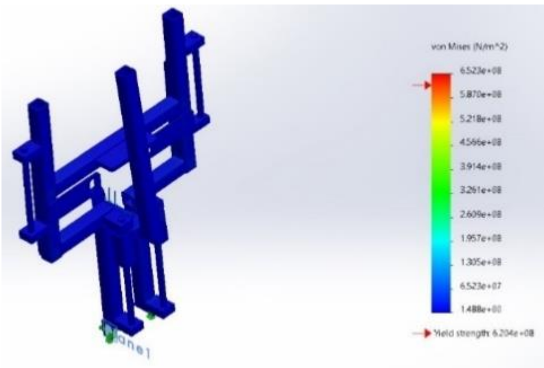
3. RESULTS AND DISCUSSION

3.1. 3D CAD simulation evaluation

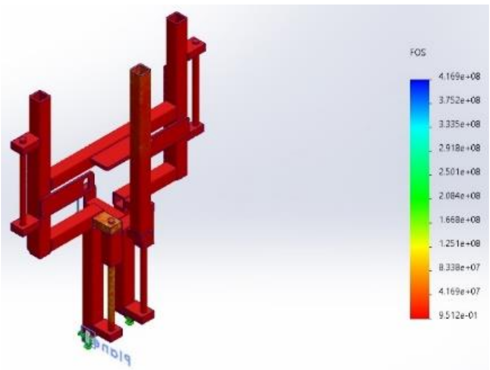
At this stage, the wheelchair design is tested using von mises stress simulation. Several weight parameters are given to test the maximum weight limit that can be handled by this tool. Table 1 presents the results of a von mises stress simulation and evaluation for varying weights. The von mises stress, measured in N/m², represents the maximum stress experienced by the material, indicating its susceptibility to failure under the given loads. Deformation scale illustrates the extent of deformation in the structure, with both minimum and maximum values provided. Resultant displacement, measured in millimeters, denotes the magnitude of displacement resulting from the applied load. Additionally, the factor of safety is presented, indicating the margin of safety between the applied load and the material's capacity to withstand it. As weight increases from 80 to 120 kg, von mises stress and resultant displacement also increase, while the factor of safety decreases, suggesting a decrease in structural stability relative to the applied load. Figure 8 shows the results of test simulations on the SolidWorks application, showcasing two critical analyses: 8(a) the von mises stress distribution, which highlights areas of maximum stress, and 8(b) the factor of safety, which evaluates the structural reliability under applied loads.

Table 1. Von Mises stress simulation and evaluation

Weight (kg)	Von Mises stress (N/m2)		Deformation scale	Resultant displacement (mm)		Factor of safety
	Min	Max		Min	Max	
80	6.196e-01	2.715e+08	62.0224	0.000e+00	1.427e+00	2.3
90	1.113e+00	4.877e+08	34.5352	0.000e+00	2.564e+00	1.3
100	1.239e+00	5.431e+08	31.0112	0.000e+00	2.855e+00	1.1
110	1.363e+00	5.974e+08	28.0192	0.000e+00	3.141e+00	1.0
120	1.488e+00	6.523e+08	25.8207	0.000e+00	3.429e+00	0.95



(a)



(b)

Figure 8. 3D CAD structure evaluation (a) von mises stress and (b) factor of safety

3.2. Field testing and data collecting

Field testing of the stair climbing wheelchair was carried out on a total of three stair and slope conditions. Figure 9 presents evidence of experiments carried out in climbing and descending steep stairs as shown in Figure 9(a) and 9(b), sloping stairs as shown in Figure 9(c), and slope conditions as shown in Figure 9(d). The dataset is taken based on these three conditions, while Figures 9(e)-9(f) are additional tests to determine the reliability of the mechanical design that has been made in passing obstacles.

(a) (b) (c)

(d) (e) (f)

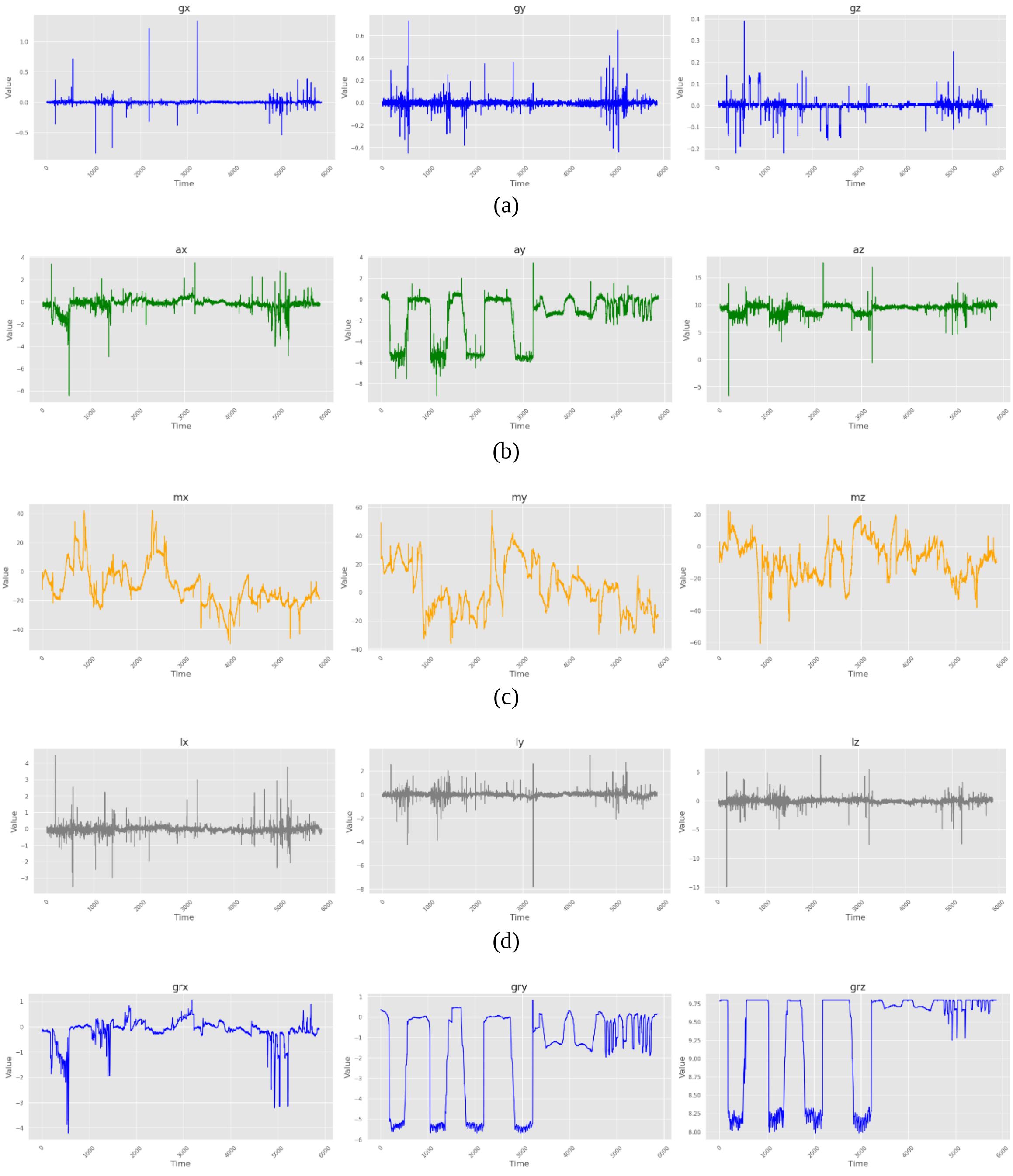
Figure 9. SCW field testing (a) up steep stairs, (b) down steep stairs, (c) sloping stairs, (d) flat derivative plane, (e) flat surface with obstacle, and (f) flat surface with obstacle diagonal view

3.3. Data visualization and analysis

The collected datasets are then combined and visualized in the form of timeseries graphs in Figure 10, highlighting various sensor data types: Figure 10(a) gyroscope data, Figure 10(b) accelerometer data, Figure 10(c) magnetometer data, Figure 10(d) linear acceleration data, and Figure 10(e) gravity data, providing a comprehensive view of the sensor readings. Sequentially, the data is grouped based on their id labels, namely i) down_stairs; ii) up_stairs; iii) down_slope; iv) up_slope; v) down_largestair; and vi) up_largestair. From this data visualization, it can be seen that several patterns are formed from several recording features. Further analysis was carried out on the correlation between data features, where there is a strong correlation between several features as presented in Figure 11.

Positive correlations suggest that when one variable increases, the other variable also tends to increase. In the context of an IMU like MPU6050, strong positive correlations could indicate synchronized movements or measurements along different axes or components. For instance, a strong positive correlation between accelerometer readings along different axes (‘ax’, ‘ay’, ‘az’) may suggest that movements in one direction are often accompanied by movements in another direction, which is common in many physical activities. Similarly, strong positive correlations between orientation readings along different axes (‘ox’, ‘oy’, ‘oz’) might indicate consistent rotations or tilting movements happening simultaneously along multiple axes.

Negative correlations indicate that as one variable increases, the other tends to decrease, and vice versa. In the context of an IMU, strong negative correlations could indicate opposing or counteracting effects between different measurements. For instance, a strong negative correlation between orientation along the z-axis (‘oz’) and accelerometer readings along the y-axis (‘ay’) might suggest that tilting or rotating the device along the z-axis leads to a decrease in acceleration along the y-axis, and vice versa. This makes sense since gravity influences both orientation and acceleration but in opposite directions. Another example could be a strong negative correlation between orientation along one axis (‘ox’, ‘oy’, ‘oz’) and gravitational readings (‘grx’, ‘gry’, ‘grz’). When the device is tilted or rotated along one axis, the gravitational readings along other axes may decrease due to the change in orientation. Based on the correlation between these features, several classification methods can be applied to determine the SCW is in certain staircase environment conditions. Therefore, the application of machine learning as a classification and prediction of ladder types is carried out in the next section.



(a) (b) (c) (d) (e)

Figure 10. SCW IMU dataset visualization (a) gyroscope, (b) accelerometer, (c) magnetometer, (d) linear, and (e) gravity data

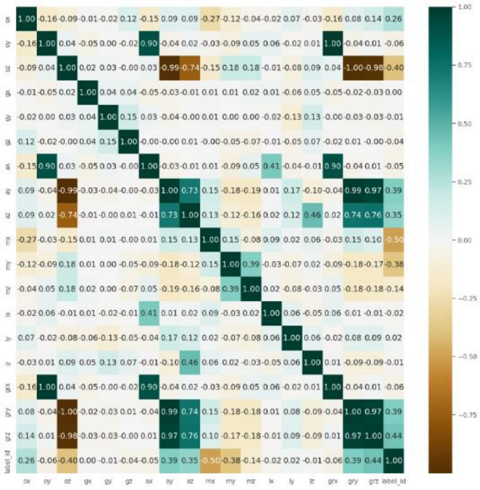


Figure 11. SCW IMU correlation matrix

3.3. Wheelchair movement and environment prediction

These results depict the accuracies of various machine learning classifiers on a dataset. Table 2 presents the evaluation metrics for various machine learning models applied to a classification task. Precision, recall, F1-score, and accuracy are reported for each model. Logistic regression achieved a precision of 0.77, recall of 0.81, F1-score of 0.79, and accuracy of 0.776, indicating moderate performance. KNN exhibited high precision (0.97) and accuracy (0.973), with slightly lower recall (0.92) and F1-score (0.95). Support vector classifier (SVC) demonstrated strong performance with a precision of 0.96, recall of 0.93, F1-score of 0.94, and accuracy of 0.946. Decision tree and random forest classifiers both achieved near-perfect scores across all metrics, indicating excellent performance. Gradient boosting classifier also performed exceptionally well with perfect scores in all metrics except for a slightly lower accuracy of 0.997. Conversely, AdaBoost classifier displayed relatively poor performance, with a precision of 0.54, recall of 0.49, F1-score of 0.45, and accuracy of 0.488. Overall, the models varied significantly in their performance, with ensemble methods generally outperforming simpler classifiers, and AdaBoost being the least effective in this particular classification task.

Table 2. Model evaluation

Model	Precision	Recall	F1-Score	Accuracy
RandomForestClassifier	1	1	1	0.9982978723404256
GradientBoostingClassifier	1	1	1	0.9974468085106383
DecisionTreeClassifier	0.98	0.96	0.97	0.9880851063829788
KNeighborsClassifier	0.97	0.92	0.95	0.9727659574468085
SVC	0.96	0.93	0.94	0.9463829787234043
LogisticRegression	0.77	0.81	0.79	0.7761702127659574
AdaBoostClassifier	0.54	0.49	0.45	0.4876595744680851

The provided AUC (area under the ROC curve) scores reveal the discriminative performance of various machine learning classifiers in binary classification tasks (Figure 12). Logistic regression demonstrates strong discriminative power with an AUC of 0.97, while K-nearest neighbors classifier achieves perfection with an AUC of 1, indicating optimal classification performance. SVC also performs exceptionally well with an AUC of 0.99, as do decision tree and random forest classifiers with AUC scores of 0.99 and 1.00, respectively. Gradient boosting classifier achieves a perfect AUC of 1.00, reflecting outstanding discriminative ability. However, AdaBoost classifier lags behind with a lower AUC of 0.85, suggesting comparatively weaker discrimination between classes. These results offer valuable insights into the efficacy of different classifiers in separating classes and can inform the selection of the most suitable model for the specific classification task at hand.

The evaluation of various machine learning classifiers, considering both AUC (area under the ROC curve) and traditional classification metrics like precision, recall, F1-score, and accuracy, provides a comprehensive understanding of their performance across different aspects of binary classification tasks. Models such as KNN and RF achieve perfection in both AUC and accuracy, indicating optimal discrimination and overall correctness in class predictions. Similarly, gradient boosting classifier exhibits excellence across all metrics, showcasing superior discriminative ability and precision in classifying instances. SVC and decision tree classifier also perform admirably, demonstrating high AUC values, strong precision, recall, F1-scores, and accuracy. Logistic regression, while achieving a slightly lower AUC compared to other top-performing models, maintains respectable performance across traditional metrics, indicating robustness in classification tasks. In contrast, AdaBoost classifier lags behind, exhibiting a lower AUC and subpar performance in precision, recall, F1-score, and accuracy.

Our findings demonstrate that the integration of a double-track mechanism with machine learning-based surface prediction significantly enhances the stability and adaptability of stair-climbing wheelchairs. Unlike previous models that rely solely on mechanical stability, our approach enables real-time adaptation to varying terrains, thereby improving both safety and user confidence. The successful implementation of machine learning in predicting surface conditions suggests promising avenues for future research. Further refinement of the algorithm and integration with advanced sensors could lead to even more responsive and intelligent mobility solutions for individuals with disabilities. Additionally, exploring the scalability of this approach for different types of urban environments and wheelchair models will be crucial. This study represents a significant advancement in the design and functionality of stair-climbing wheelchairs, offering a practical solution to the challenges of urban mobility for individuals with disabilities. The integration of machine learning for surface prediction sets the stage for the development of more intelligent, adaptable, and user-friendly mobility devices.

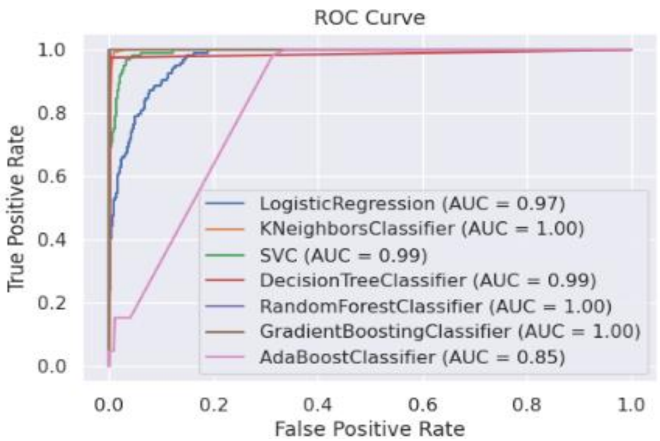


Figure 12. ROC curve and AUC graph

4. CONCLUSION

This study examines the key obstacles related to safety and ease of use for individuals utilising personal mobility wheelchairs in urban settings, with a specific emphasis on equipment designed to climb stairs. The research employs a comprehensive strategy that integrates theoretical dynamic analysis, hardware design and simulation, field testing, and machine learning categorisation to enhance the design, performance, and prediction capabilities of these wheelchairs. Theoretical analysis has played a vital role in guaranteeing stability and flexibility in various environments, establishing a strong basis for practical implementation. The utilisation of SolidWorks for hardware design and simulations has yielded significant insights into the structural integrity, facilitating essential modifications. The design’s effectiveness has been proven by real-world validation, which involved field testing on different stair and slope circumstances. Additionally, reliable environmental classification has been made possible by collecting data from IMU sensors. Machine learning models, such as RF, gradient boosting, and decision tree classifiers, have shown great accuracy and precision in predicting movement conditions. This progress has opened up possibilities for creating intelligent wheelchairs that can safely and efficiently navigate urban environments.

The importance of these discoveries rests in their ability to improve the safety and autonomy of people with mobility limitations in difficult urban environments. This study not only enhances the technology of mobility aids but also contributes to the broader objective of developing more inclusive and accessible urban environments. Future research should prioritise the improvement of designs, the incorporation of cutting-edge sensor technologies, and the exploration of innovative machine learning methods to further optimise performance. Furthermore, conducting tests in diverse and unregulated settings will be essential to guarantee the scalability and practicality of these advancements in real-world scenarios. This continuing project has the potential to greatly enhance the quality of life for users, by making urban mobility safer and more accessible for everyone.

ACKNOWLEDGEMENTS

Sincere gratitude extended to Rajamangala University of Technology Thanyaburi for their support and provision of facilities during the course of this research. The access to resources and infrastructure offered by the university has significantly contributed to the success and quality of this research.

REFERENCES

[1] S. Alqahtani *et al.*, "Stakeholder perspectives on research and development priorities for mobility assistive-technology: a literature review," *Disability and Rehabilitation: Assistive Technology*, vol. 16, no. 4, pp. 362–376, May 2021, doi: 10.1080/17483107.2019.1650300.

[2] S. Paiva, M. Ahad, G. Tripathi, N. Feroz, and G. Casalino, "Enabling technologies for urban smart mobility: recent trends, opportunities and challenges," *Sensors*, vol. 21, no. 6, Mar. 2021, doi: 10.3390/s21062143.

[3] D. L. Marques and M. C. Coelho, "A literature review of emerging research needs for micromobility-integration through a life cycle thinking approach," *Future Transportation*, vol. 2, no. 1, pp. 135–164, Feb. 2022, doi: 10.3390/futuretransp2010008.

[4] K. D. Klinich, M. A. Manary, N. R. Orton, K. J. Boyle, and J. Hu, "A literature review of wheelchair transportation safety relevant to automated vehicles," *International Journal of Environmental Research and Public Health*, vol. 19, no. 3, 2022, doi: 10.3390/ijerph19031633.

[5] C. Deng, Y. Zhang, D. Yang, H. Zhang, and M. Zhu, "Recent progress on barium titanate-based ferroelectrics for sensor applications," *Advanced Sensor Research*, vol. 3, no. 6, Jun. 2024, doi: 10.1002/adsr.202300168.

[6] W. Tao, J. Xu, and T. Liu, "Electric-powered wheelchair with stair-climbing ability," *International Journal of Advanced Robotic Systems*, vol. 14, no. 4, Jul. 2017, doi: 10.1177/1729881417721436.

[7] B. Sharma, B. M. Pillai, K. Borvorntanajanya, and J. Suthakorn, "Modeling and design of a stair climbing wheelchair with pose estimation and adjustment," *Journal of Intelligent and Robotic Systems*, vol. 106, no. 3, Nov. 2022, doi: 10.1007/s10846-022-01765-3.

[8] Y. Li *et al.*, "Kinematic modeling of a combined system of multiple mecanum-wheeled robots with velocity compensation," *Sensors*, vol. 20, no. 1, Dec. 2019, doi: 10.3390/s20010075.

[9] Y. Gong *et al.*, "Legged robots for object manipulation: a review," *arXiv preprint arXiv:2303.16865*, Mar. 2023.

[10] A. Thoesen and H. Marvi, "Planetary surface mobility and exploration: a review," *Current Robotics Reports*, vol. 2, no. 3, pp. 239–249, 2021, doi: 10.1007/s43154-021-00056-3.

[11] S. Sivakanthan *et al.*, "Automated curb recognition and negotiation for robotic wheelchairs," *Sensors*, vol. 21, no. 23, Nov. 2021, doi: 10.3390/s21237810.

[12] S. Desai, S. Mantha, and V. Phalle, "Design of a reconfigurable wheelchair with stand-sit-sleep capabilities for enhanced independence of long-term wheelchair users," *Technology and Disability*, vol. 30, no. 3, pp. 135–151, Nov. 2018, doi: 10.3233/TAD-180210.

[13] A. Pappalettera, G. Reina, and G. Mantriota, "Design and analysis of tracked stair-climbing robot using innovative suspension system," *Robotics*, vol. 13, no. 3, Mar. 2024, doi: 10.3390/robotics13030045.

[14] T. Seo, S. Ryu, J. H. Won, Y. Kim, and H. S. Kim, "Stair-climbing robots: a review on mechanism, sensing, and performance evaluation," *IEEE Access*, vol. 11, pp. 60539–60561, 2023, doi: 10.1109/ACCESS.2023.3286871.

[15] A. Botta, R. Bellincioni, and G. Quaglia, "Autonomous detection and ascent of a step for an electric wheelchair," *Mechatronics*, vol. 86, Oct. 2022, doi: 10.1016/j.mechatronics.2022.102838.

[16] J. P. Fredericks, S. Visagie, and L. van Niekerk, "A qualitative exploration of community mobility experiences of wheelchair users," *African Journal of Disability*, vol. 13, 2024, doi: 10.4102/AJOD.V13I0.1253.

[17] R.-C. Chen, C. Dewi, S.-W. Huang, and R. E. Caraka, "Selecting critical features for data classification based on machine learning methods," *Journal of Big Data*, vol. 7, no. 1, Dec. 2020, doi: 10.1186/s40537-020-00327-4.

[18] R. Sun, G. Wang, W. Zhang, L.-T. Hsu, and W. Y. Ochieng, "A gradient boosting decision tree based GPS signal reception classification algorithm," *Applied Soft Computing*, vol. 86, Jan. 2020, doi: 10.1016/j.asoc.2019.105942.

[19] A. N. Beskopylny *et al.*, "Concrete strength prediction using machine learning methods catboost, k-nearest neighbors, support vector regression," *Applied Sciences*, vol. 12, no. 21, Oct. 2022, doi: 10.3390/app122110864.

[20] A. Hashemizadeh, A. Maaref, M. Shateri, A. Larestani, and A. Hemmati-Sarapardeh, "Experimental measurement and modeling of water-based drilling mud density using adaptive boosting decision tree, support vector machine, and K-nearest neighbors: A case study from the South Pars gas field," *Journal of Petroleum Science and Engineering*, vol. 207, Dec. 2021, doi: 10.1016/j.petrol.2021.109132.

[21] M. A. Afrianto and M. Wasesa, "Booking prediction models for peer-to-peer accommodation listings using logistics regression, decision tree, k-nearest neighbor, and random forest classifiers," *Journal of Information Systems Engineering and Business Intelligence*, vol. 6, no. 2, Oct. 2020, doi: 10.20473/jisebi.6.2.123-132.

[22] L. J. Muhammad, E. A. Algehyne, and S. S. Usman, "Predictive supervised machine learning models for diabetes mellitus," *SN Computer Science*, vol. 1, no. 5, Sep. 2020, doi: 10.1007/s42979-020-00250-8.

[23] J. Krohkaew, P. Nilaphruek, N. Witthayawiroj, S. Uapipatanakul, Y. Thwe, and P. N. Crisnapati, "Thailand raw water quality dataset analysis and evaluation," *Data*, vol. 8, no. 9, Sep. 2023, doi: 10.3390/data8090141.

[24] F. Thabtah, S. Hammoud, F. Kamalov, and A. Gonsalves, "Data imbalance in classification: Experimental evaluation," *Information Sciences*, vol. 513, pp. 429–441, Mar. 2020, doi: 10.1016/j.ins.2019.11.004.

[25] Ž. Đ. Vujovic, "Classification model evaluation metrics," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 6, 2021, doi: 10.14569/IJACSA.2021.0120670.

BIOGRAPHIES OF AUTHORS

Pharan Chawaphan earned his bachelor's degree in Power Electronics Engineering Technology in 2015 from King Mongkut's University of Technology in North Bangkok. He furthered his education with a master's degree in Control Science and Engineering, which he earned in 2018 from the South China University of Technology. He is currently pursuing a Doctoral of Engineering in Mechatronics Engineering at Rajamangala University of Technology Thanyaburi. His research interests are broad and interdisciplinary, spanning mechatronics, control systems, and power electronics. He can be contacted by email: pharan_c@mail.rmutt.ac.th.

Dechrit Maneetham currently serves as an Associate Professor in Mechatronics Engineering at Rajamangala University of Technology in Thanyaburi, Thailand. His academic journey includes earning B. Ind.Tech. in Material Handling Technology and M.S. in Mechanical Engineering from King Mongkut's University of Technology in North Bangkok. In 2010, he achieved a D.Eng. in Mechatronics from the Asian Institute of Technology, followed by a Ph.D. in Electrical and Computer Engineering from Mahasarakham University in 2018. With a wealth of experience exceeding 15 years in teaching engineering, he has significantly contributed to the field. His contributions extend to the publication of over 30 technical papers. Beyond academia, he has shared his knowledge through robotics short courses at various conferences and authored seven books. These publications cover a range of topics, including pneumatics system, hydraulics system, MCS-51 microcontroller, PIC microcontroller, Arduino microcontroller, PLC beckhoff, and robot. These works showcase his expertise in the realms of robotics, automation, mechatronics, and biomedical applications. He can be contacted at email: dechrit_m@rmutt.ac.th.

Padma Nyoman Crisnapati earned his bachelor's degree in 2009 from the Department of Informatics Engineering at Sepuluh Nopember Institute of Technology. Subsequently, he pursued a master's degree in Learning Technology in 2011 and another master's degree in computer science in 2018, both from Ganesha Education University. He successfully earned a D.Eng. in the Mechatronics Engineering Department at Rajamangala University of Technology Thanyaburi (RMUTT). His diverse research interests encompass various domains, including mechatronics, robotics, automation, augmented and virtual reality, 2D and 3D animation, and internet of things. He can be contacted at email: crisnapati@rmutt.ac.th.