INTEGRATING EDGE AI VISION FOR RELIABLE PATH TRACKING IN AUTOMATED GUIDED VEHICLES

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ABSTRACT: Conventional automated guided vehicles (AGVs) frequently lack adaptability in dynamic Industry 4.0 environments due to their reliance on basic sensor arrays and centralized processing. This study investigates the enhancement of an AGV through the integration of an Edge Artificial Intelligence (AI) vision module, leveraging decentralized Edge AI for real-time on-device inference to eliminate centralized processing latency, to evaluate its operational performance and reliability. A baseline AGV utilizing infrared line sensors and ultrasonic obstacle detection was empirically compared against an enhanced AGV equipped with a HuskyLens vision module on an identical chassis. Systematic evaluations were conducted across multiple performance metrics under controlled conditions. The experimental results indicate that both systems exhibited comparable reliability in line-tracking success (95% for the baseline versus 91% for the AI-enhanced AGV) and obstacle detection rates (90% versus 93%, respectively). However, the integration of Edge AI introduced operational trade-offs, evidenced by an increased mean lap travel time (20.46 s compared to 16.38 s) and a reduced battery endurance (31.3 min compared to 43.6 min) owing to higher computational demands. Despite these constraints, the enhanced AGV successfully demonstrated advanced capabilities, including object classification and face recognition, highlighting the potential of Edge AI for executing complex autonomous tasks.

KEYWORDS: *Automated Guided Vehicle (AGV); Edge Artificial Intelligence; Vision-Based Navigation; Performance Analysis; Industry 4.0*

1.0 INTRODUCTION

Automated Guided Vehicles (AGVs) have become increasingly important in modern manufacturing and logistics operations. Initially developed as simple machines that followed physical guide paths on the ground, AGV technology has progressively evolved, enabling the vehicles to make independent decisions and avoid obstacles without human intervention [1-2]. Recently, Edge Artificial Intelligence (Edge AI) has emerged as a crucial technology to facilitate these advanced capabilities. Fundamentally, Edge AI is defined by on-device inference, a computational paradigm that shifts execution workloads from centralized remote servers or cloud environments directly to the physical microcontroller on the robot.

As demonstrated by Yan et al. [3], Edge AI processes data directly on the robot locally, thereby reducing transmission delays and rendering the AGVs faster and more reliable in dynamic, high-traffic environments [4-5]. These features are essential in advanced factories where AGVs are required to continuously interact with their surroundings to execute tasks efficiently. Furthermore, the integration of vision-based systems provides advanced image processing functionalities. Modules such as HuskyLens enable the AGV to move and respond to its surroundings with high precision [6]. Sugiarto [7] and Aslan et al. [8] assert that image processing allows the AGV to see objects and understand its environment, which fundamentally improves its operational performance. Davoudi and Heidarian [9] and Ma'arif et al. [10] highlight that real-time image processing helps the robot find and follow objects, thereby improving how the AGV navigates and avoids obstacles. Liu et al. [11] further emphasize that processing data locally makes the system notably faster and less dependent on external, centralized networks.

Despite the recognized benefits of integrating Edge AI and advanced vision systems, conventional AGVs still face major operational limitations. Conventional AGVs predominantly rely on simple line-following systems utilizing infrared or magnetic sensors. According to Hrušecká and Lopes [12] and Aryanti [13], these conventional systems are frequently ineffective when subjected to varying light conditions, complex path layouts, or unexpected obstacles. Furthermore, conventional systems are typically managed by centralized processing architectures. Rahman et al. [14] and Abderrahim et al. [15] note that this centralized approach leads to processing delays that are highly inefficient in advanced factories where real-time, instantaneous responses are required. While new technologies and machine learning have been proposed by researchers like Vlachos et al. [16] and Fu et al. [17] to reduce delays and make AGVs more efficient, a substantial research gap remains. Technologies combining different sensors, known as sensor fusion, have been proposed by Bach and Yi [18] and Gomes et al. [19] to help AGVs better navigate challenging environments. However, existing studies typically evaluate either traditional AGVs or AI-enhanced systems in isolation, rarely comparing both methodologies on identical platforms under consistent environmental conditions. This gap highlights the necessity for direct, empirical benchmarking to assess how Edge AI integration explicitly affects operational performance and reliability.

Therefore, to address the lack of direct comparative studies in existing literature, the objective of this study is to evaluate and compare the performance and reliability of an AGV with and without Edge AI integration. In selecting the navigation control framework, complete computational decentralization was prioritized to establish localized, on-device decision-making, thereby bypassing the centralized communication bottlenecks and transmission latencies inherent in conventional centralized architectures. To achieve this comparative evaluation, an enhanced AGV capable of line tracking, obstacle avoidance and basic navigation is designed and developed using MakeCode micro:bit and the HuskyLens module. Then, the positioning and navigation results of a baseline AGV (without Edge AI) and the enhanced AGV (with Edge AI) are assessed under identical controlled conditions. The experimental evaluations are systematically conducted across several performance metrics, including line tracking success rate, travel time, power consumption, response to varying light intensities and the impact of motor speed on tracking stability. Finally, additional AI capabilities of the Edge AI vision module, such as object recognition, face detection, tag recognition and color detection, are demonstrated to highlight its potential for executing advanced autonomous tasks beyond basic navigation.

2.0 METHODOLOGY

The methodology of this study was designed to empirically evaluate and compare the operational performance and reliability of a baseline automated guided vehicle (AGV) against an enhanced AGV integrated with Edge Artificial Intelligence (AI). The approach encompasses the proposed algorithmic and computational navigation method, the system design, the configuration of the experimental setup, and the systematic data collection and analysis procedures.

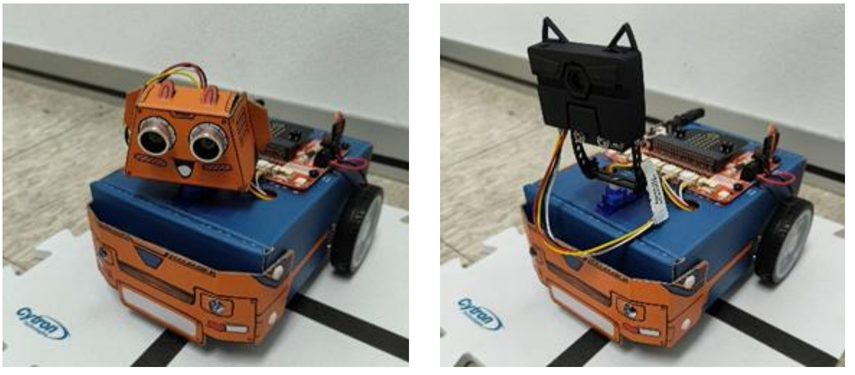
2.1 Proposed Computational Method Relying on Decentralized Inference

The core computational method proposed in this research relies on decentralized, on-device Edge AI to execute real-time path tracking and perception without remote network dependencies. Fundamentally, the method bypasses the latency of centralized architectures by executing deep learning computer vision algorithms locally within the perceptual cycle of the vehicle.

Under nominal tracking conditions, the primary navigation pipeline utilizes on-device visual line tracking. The onboard camera captures real-time video frames of the track, and the built-in vision processor executes edge-detection and line-extraction algorithms to identify the trajectory. When a suspicious object is detected, the visual sensor operates in Object Tracking mode. Because the visual processing unit must redirect computational resources to identify and track the bounding box of the obstacle, path-tracking coordinate updates are temporarily throttled. During this phase of concurrent visual tasking, the primary trajectory alignment is automatically handed off to the active IR sensor fallback system. This hybrid method allows the vehicle to execute high-level cognitive tasks (such as obstacle discrimination and feature tracking) while maintaining low-level motor stability and path tracking.

2.2 System Design and Hardware Configuration

To ensure a consistent comparative analysis, both AGV platforms were constructed using an identical mechanical architecture, including the ZOOM:BIT Robot Car chassis, a Micro:bit v2 microcontroller, dual-axis TT gear motors, a REKA:BIT expansion board and 1.5V AA rechargeable batteries. Figure 1 shows the complete setup of both AGV 1 and AGV 2. First, the baseline system (AGV 1) was configured utilizing a conventional 5-element MakerLine infrared sensor for line tracking and an SR04P ultrasonic sensor for obstacle detection. Second, the enhanced system (AGV 2) was configured by replacing the ultrasonic sensor with a HuskyLens Edge AI vision module. The HuskyLens module was connected via the I2C communication protocol to provide vision-based line tracking and object recognition through real-time onboard image processing. To maintain path alignment while the HuskyLens focused on object recognition, a MakerLine sensor was retained on AGV 2 as a fallback system.



(a) AGV 1 setup (b) AGV 2 setup

Figure 1: Complete setup of the (a) baseline system (AGV 1); and (b) the Edge AI-enhanced system (AGV 2)

2.3 Software Implementation and Control Logic

Both AGV configurations were programmed using the Microsoft MakeCode platform to ensure that performance disparities were attributable to the sensing methods rather than algorithmic complexities. The detailed algorithmic difference between the baseline and Edge AI-enhanced systems is structured as shown in Figure 2. For AGV 1, a block-based conditional if-else structure was utilized to process inputs from the infrared sensor array; motor speeds were dynamically adjusted based on which specific segment detected the line. Obstacle avoidance was executed by continuously measuring the distance to objects and halting the motors when a predefined threshold was breached.

Conversely, AGV 2 utilized the HuskyLens operating in Line Tracking mode, where the Micro:bit adjusted motor speeds based on the X-axis coordinate of the line within the camera frame. For obstacle detection, the HuskyLens was operated in Object Tracking mode; upon visual recognition of an object, the system was programmed to halt immediately and emit a multi-tone warning signal to prevent collisions.

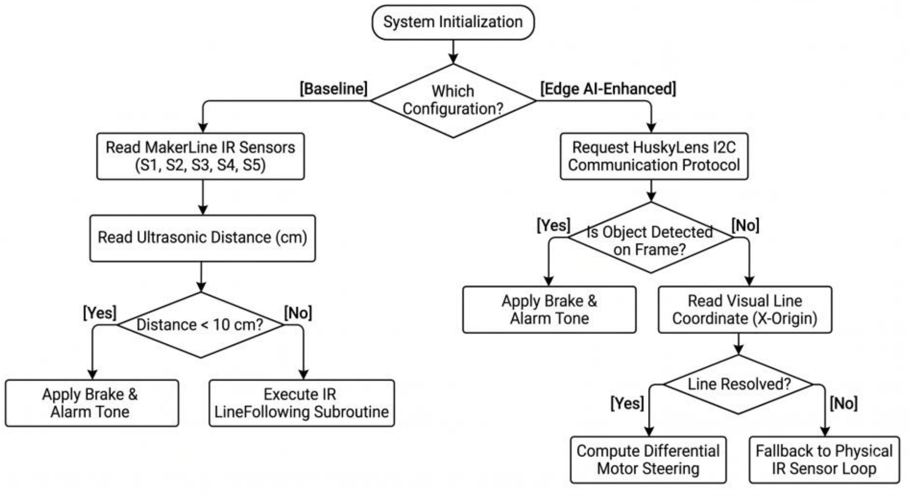


Figure 2: Detailed algorithmic difference between the baseline and Edge AI-enhanced systems

2.4 Experimental Setup and Environmental Parameters

The experimental test track was constructed using modular interlocking EVA foam tiles (315 mm × 315 mm × 10 mm) featuring a continuous 3.8-meter loop comprising straight sections, curved turns and a cross junction as shown in Figure 3. The navigation path was delineated by an 18 mm wide black line. All experiments were systematically conducted in a controlled indoor laboratory environment to regulate ambient parameters. Constant fluorescent lighting, flat non-reflective surfaces and fixed stationary obstacles were maintained to minimize unwanted variables.

Figure 3: Layout of the experimental test track

2.5 Experimental Procedures and Statistical Analysis

The experimental evaluation was systematically conducted across six primary experiments, accompanied by an additional qualitative demonstration of advanced AI capabilities. The performance metrics evaluated are shown in Table 1.

Table 1: Performance metrics evaluated

Exp	Performance metric	Description
1	Line tracking reliability	Measured by the percentage of successful laps completed over 10 trials.
2	Travel time per lap	Calculated by measuring the time required to successfully complete individual laps.
3	Battery runtime	Evaluated by running the AGVs continuously until functional depletion occurred.
4	Obstacle avoidance	Measured by the success rate of detecting and halting for a stationary obstacle placed at a predefined corner.
5	Light intensity response	Assessed by recording the binary success rate under varying ambient lighting conditions (0 lux, 10 lux, 160 lux, and 300 lux) with the onboard LED module activated and deactivated.
6	Effect of motor speed	Evaluated by incrementally adjusting motor speeds (from 25 to 250 units for 10 runs each) to identify tracking stability limits.

For Experiments 1 to 4, an Independent Samples t-test (Welch's test, assuming unequal variances, $\alpha = 0.05$) was performed to compare the mean performances of AGV 1 and AGV 2. For Experiment 5, descriptive statistics were applied to summarize the binary pass/fail outcomes. Furthermore, for Experiment 6, Pearson's correlation coefficient and trendline analysis were executed to quantify the relationship between incremental motor speed and navigation success. Finally, AGV 2 was subjected to a series of high-level industrial automation tasks using varied custom track layouts and sample objects to qualitatively validate the Edge AI module's proficiency in advanced tasks such as facial recognition, color detection and object classification.

3.0 RESULTS AND DISCUSSION

The empirical results obtained from the systematic evaluation of the baseline automated guided vehicle (AGV 1) and the Edge AI-enhanced system (AGV 2) are presented and analysed in this section. The performance of both systems is compared across six primary metrics, followed by a qualitative assessment of the advanced capabilities enabled by the vision module.

3.1 Line Tracking Reliability and Travel Time Per Lap

Table 2 presents the detailed results of the line tracking reliability and travel time per lap experiments.

Table 2: Line tracking reliability and travel time per lap results for AGV 1 and AGV 2

Trial	Line tracking reliability (%)		Travel time per lap (s)	
	AGV 1	AGV 2	AGV 1	AGV 2
1	100	90	16.3	19.5
2	90	90	17.1	20.6
3	100	80	16.1	19.6
4	100	100	15.9	21.2
5	90	90	17.2	20.1
6	100	90	16.2	20.7
7	90	100	16.5	18.8
8	100	80	16.0	20.3
9	80	100	16.4	21.5
10	100	90	16.1	22.3
Mean	95	91	16.38	20.46
Std. dev.	0.707106	0.737865	0.444222	1.036232
t-test	0.231756		6.96207×10^{-8}	

The experimental evaluation demonstrated that both AGV platforms exhibited high reliability in following the delineated track. AGV 1 achieved a mean success rate of 95%, whereas AGV 2 recorded a success rate of 91%. The calculated p-value of 0.232 confirms that this performance variance is not statistically significant under the tested conditions. The slight reduction in reliability for the AI-enhanced system is attributed to its dependence on a stable visual field [18-19]; during tight curves or mechanical vibrations, the HuskyLens camera momentarily loses line detection. In contrast, the conventional infrared array utilized by AGV 1 detects contrast changes directly [20-21] and is therefore less susceptible to angular shifts and vibrations.

Significant disparities were observed in the operational speed of the two systems. AGV 1 completed the navigation loop with a mean travel time of 16.38 s, whereas AGV 2 averaged 20.46 s. This difference is highly significant statistically ($p = 6.96 \times 10^{-8}$). The slower travel time for AGV 2 is a direct consequence of the computational demands introduced by the Edge AI module. The continuous capturing of images, execution of recognition algorithms, and transmission of steering coordinates induce accumulated processing latency during each lap [19, 22]. Furthermore, the smaller standard deviation observed for AGV 1 indicates greater speed consistency, which is highly advantageous for industrial applications requiring predictable cycle times.

To further illustrate the processing latency introduced by the Edge AI module, a box-and-whisker plot (Figure 4) was generated to visualize the statistical distribution of lap travel times. The data reveals that AGV 1 completed the navigation loop with a highly consistent mean travel time of 16.38 s and a narrow standard deviation of 0.44 s. In contrast, the continuous computational demands of real-time image processing in AGV 2 resulted in a wider data spread and an increased mean travel time of 20.46 s, alongside a higher standard deviation of 1.04 s. This statistically significant shift ($p = 6.96 \times 10^{-8}$) visually confirms the accumulated processing latency inherent to decentralized on-device inference during each lap.

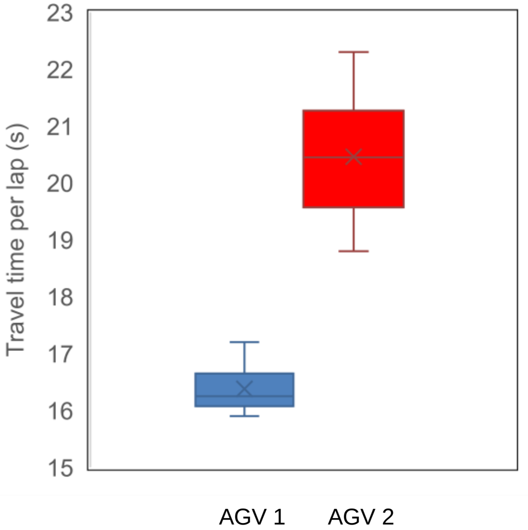


Figure 4: Box-and-whisker plot illustrating the statistical distribution of travel time per lap

3.2 Battery Runtime and Obstacle Avoidance

Table 3 presents the detailed results of the battery runtime and obstacle avoidance experiments.

Table 3: Battery runtime and obstacle avoidance results for AGV 1 and AGV 2

Trial	Battery runtime (min.)		Obstacle avoidance (success detection per 10 laps)	
	AGV 1	AGV 2	AGV 1	AGV 2
1	47	33	9	10
2	42	30	9	10
3	46	28	10	10
4	39	32	10	9
5	44	34	9	8
6	41	31	8	10
7	46	29	10	9
8	48	34	9	10
9	43	30	8	8
10	40	32	8	9
Mean	43.6	31.3	9	9.3
Std.dev.	3.098386	2.057507	0.816497	0.823273
t-test	1.83202×10^{-8}		0.423953	

The integration of Edge AI substantially impacted the power efficiency of the vehicle. AGV 1 sustained continuous operation for an average of 43.6 minutes, compared to only 31.3 minutes for AGV 2. This performance reduction ($p = 1.83 \times 10^{-8}$) highlights the high energy consumption inherent to onboard image processing. Unlike the passive infrared sensor, which requires minimal processing to detect contrast, the vision module functions simultaneously as a camera and a computational processor, thereby drawing significantly more electrical current [23].

Both systems successfully detected and halted for stationary obstacles, with AGV 1 recording a 90% mean success rate and AGV 2 achieving 93%. While this difference is not statistically significant ($p = 0.424$), the slightly superior performance of AGV 2 is linked to the wider field of view provided by the HuskyLens, which enables the visual recognition of obstacles earlier than the narrow detection cone of the ultrasonic sensor. However, it was noted that both systems were programmed with a basic binary stop-and-wait response; the advanced sensing capabilities of the AI module are not fully maximized without the implementation of sophisticated path-planning or rerouting algorithms [11].

3.3 Light Intensity Response and Effect of Motor Speed

Tables 4 and 5 present the detailed results of the battery runtime and obstacle avoidance experiments.

Table 4: Light intensity response result for AGV 1 and AGV 2

Condition	AGV 1		AGV 2	
	LED OFF	LED ON	LED OFF	LED ON
No Light (0 lux)	Pass	Pass	Fail	Pass
Low Light (10 lux)	Pass	Pass	Fail	Pass
Medium Light (160 lux)	Pass	Pass	Pass	Pass
High Light (300 lux)	Pass	Pass	Pass	Pass

Table 5: Effect of motor speed result for AGV 1 and AGV 2

Motor speed	Tracking success rate for 10 runs (%)	
	AGV 1	AGV 2
25	0	0
50	0	0
75	100	100
100	100	100
125	100	90
150	100	90
175	90	60
200	80	30
225	80	0
250	70	0
Pearson's correlation	0.493863	-0.189656

The systems exhibited contrasting responses to variations in ambient illumination. AGV 1 functioned flawlessly across all lighting spectrums, ranging from 0 lux (total darkness) to 300 lux (high intensity). This stability is achieved because infrared sensors actively emit their own signal and detect the reflection, rendering them independent of ambient light [24]. Conversely, AGV 2 failed to navigate at 0 lux without the activation of the auxiliary LED module, confirming that vision-based systems are highly sensitive to environmental lighting and require supplementary illumination to function in low-light industrial settings [18].

The evaluation of motor speed limits revealed a non-linear relationship between velocity and tracking success as shown in Figure 5. Both systems failed to operate reliably at the lowest speeds (25 and 50 units) due to insufficient motor torque. Optimal tracking was achieved between 75 and 125 units. At speeds exceeding 125 units, the accuracy of AGV 2 degraded sharply compared to the baseline system. Statistical analysis quantified this divergence, showing a positive correlation (0.49) for AGV 1, suggesting that a certain level of speed actually helps with smoother tracking, while a negative correlation (-0.19) for AGV 2, indicating that going faster tends to reduce tracking accuracy. The polynomial regression model yields a coefficient of determination (R^2

≈0.75), mathematically validating a non-linear relationship between motor speed and tracking success. As velocity increases, the vision module has insufficient time to capture and process frames, causing a critical lag in steering commands, similarly to the studies conducted by Puppim de Oliveira et al. [19]. The infrared sensor, conversely, reacts almost instantaneously, maintaining high stability at elevated speeds.

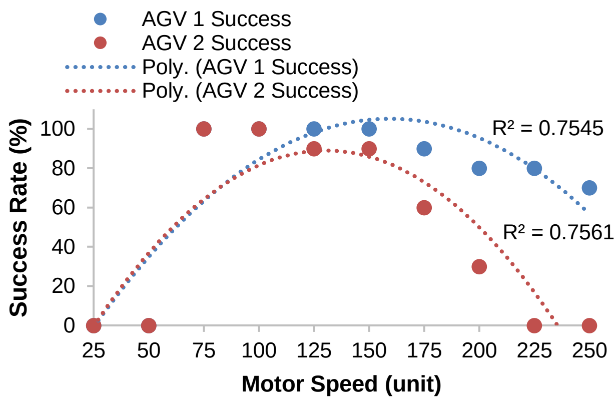
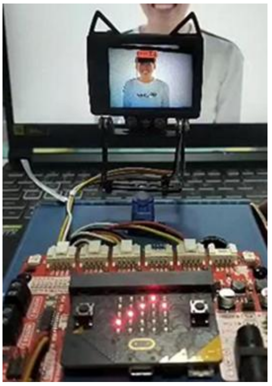


Figure 5: Relationship of motor speed and tracking success rate for AGV 1 and AGV 2

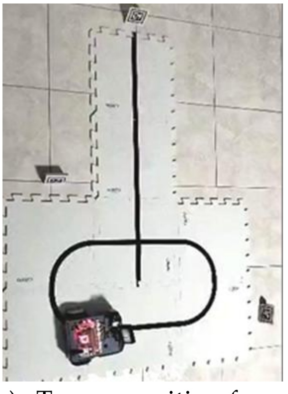
3.4 Real-Time On-Device Biometric Verification, Color-Signal Interpretation, Adaptive Routing and Sorting

To contextualize the operational trade-offs identified in the preceding metrics, the expanded capabilities of the Edge AI module were qualitatively demonstrated as shown in Figure 6. Unlike the conventional AGV, the AI-enhanced system successfully executed complex autonomous tasks, including facial recognition for secure access control, color detection for interpreting traffic signals, tag recognition for flexible routing and object classification for sorting applications. These features align with recent developments in AI-driven robotics [25, 26], where vision-based systems enable advanced interaction and task flexibility.

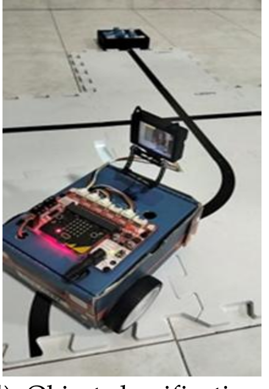


(a) Face recognition for secure access control

(b) Color recognition for interpreting traffic signals



(c) Tag recognition for flexible routing tasks



(d) Object classification for identifying sample items

Figure 6: Series of high-level industrial automation tasks for AGV 2 executing (a) face recognition; (b) color recognition; (c) tag recognition; and (d) object classification tasks

The results establish that while Edge AI integration introduces constraints in power efficiency and processing speed [23], it significantly broadens the functional adaptability of AGVs for advanced Industry 4.0 environments.

4.0 CONCLUSION

This study successfully evaluated the enhancement of an AGV through the integration of an Edge AI vision module, systematically comparing its operational performance and reliability against a conventional sensor-based system. The primary research objectives were fully realized through a systematic, empirical benchmarking framework that evaluated the vehicle's operational capabilities across six critical performance metrics. The experimental results demonstrated that the AI-enhanced AGV achieved comparable reliability in line tracking success (91% versus 95%) and obstacle detection rates (93% versus 90%) when compared to the baseline AGV. However, the integration of Edge AI introduced notable operational constraints, specifically yielding increased lap travel times (20.46 s versus 16.38 s) and substantially reduced battery endurance (31.3 min versus 43.6 min) owing to the continuous computational demands of real-time image processing. Furthermore, the vision-based system exhibited a high sensitivity to variations in ambient lighting conditions. Despite these constraints, the Edge AI module successfully executed advanced autonomous capabilities, including object classification, facial recognition, tag reading and color detection. These findings confirm that while conventional AGVs remain highly efficient for simple, predictable operations, Edge AI integration significantly broadens the functional adaptability and intelligence required for dynamic Industry 4.0 environments.

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AUTHOR CONTRIBUTIONS

M.N. Maslan: Conceptualization, Data Curation, Validation, Writing- Reviewing and Editing, Supervision; Y.H. Chung: Methodology, Software, Data Collection, Writing- Original Draft Preparation; L. Abdullah: Validation, Writing- Reviewing and Editing; A.S. Nur Chairat: Analysis and Interpretation of Results; F. Yakub: Investigation, Writing- Reviewing and Editing.

CONFLICTS OF INTEREST

The manuscript has not been published elsewhere and is not under consideration by other journals. All authors have approved the review, agree with its submission and declare no conflict of interest on the manuscript.

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