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Edge AI-Powered Obstacle Detection and Efficiency Analysis in Autonomous Lawn Mowers for Smart Agriculture

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Abstract

The demand for autonomous agricultural machines is increasing with the global push toward smart farming and sustainable land management. This study showcases a framework for obstacle detection and efficiency analysis in an autonomous lawn mower, utilizing Edge AI technology. The system employs a pruned MobileNetV2 convolutional neural network operating on an ESP32-CAM alongside ultrasonic sensors for instantaneous obstacle recognition, attaining 92.3% classification accuracy, a macro-averaged AUROC of 0.94, and a mean Average Precision (mAP) of 0.92, with an inference latency of 85 ms per frame (approximately 11.8 FPS). Field trials were carried out at two locations featuring 12 randomized plots (10 m × 10 m each) following a 3 × 2 × 2 factorial design (vegetation height: short/medium/tall; terrain: level/uneven; moisture: dry/wet) with five repeats per condition (totaling 120 trials). The mower reached a theoretical maximum field capacity (FCt) of 1.23 ha/hr, an actual field capacity (FCe) of 1.05 ha/hr, and a peak field efficiency (η) of 85.4% ± 2.3% CI on short, flat, dry areas. Efficiency decreased to 71.0% ± 3.5% CI on high, irregular, damp areas. ANOVA validated substantial impacts of surface ($p < 0.01$, $\eta^2 = 0.21$), grass height ($p < 0.01$, $\eta^2 = 0.18$), and moisture ($p < 0.05$, $\eta^2 = 0.11$) on efficiency. An ablation study indicated that excluding ultrasonic sensors decreased AUROC from 0.94 to 0.86, whereas enhancing image resolution from 224 × 224 to 320 × 320 px raised IoU from 0.78 to 0.82 but boosted latency from 85 ms to 124 ms. Analysis of failures showed that obstacle misclassification happened in 4% of trials, low-light inaccuracies in 6%, ultrasonic blind spots in 5%, and slippage on wet grass in 3%, all countered by built-in safety interlocks. The findings indicate that the suggested system merges real-time Edge AI perception with quantitative analysis of field efficiency, offering a scalable and secure framework for intelligent lawn mower. Future extensions will explore multi-sensor fusion, SLAM-based navigation, and autonomous docking/charging to enable fully autonomous, continuous operation in diverse outdoor environments.

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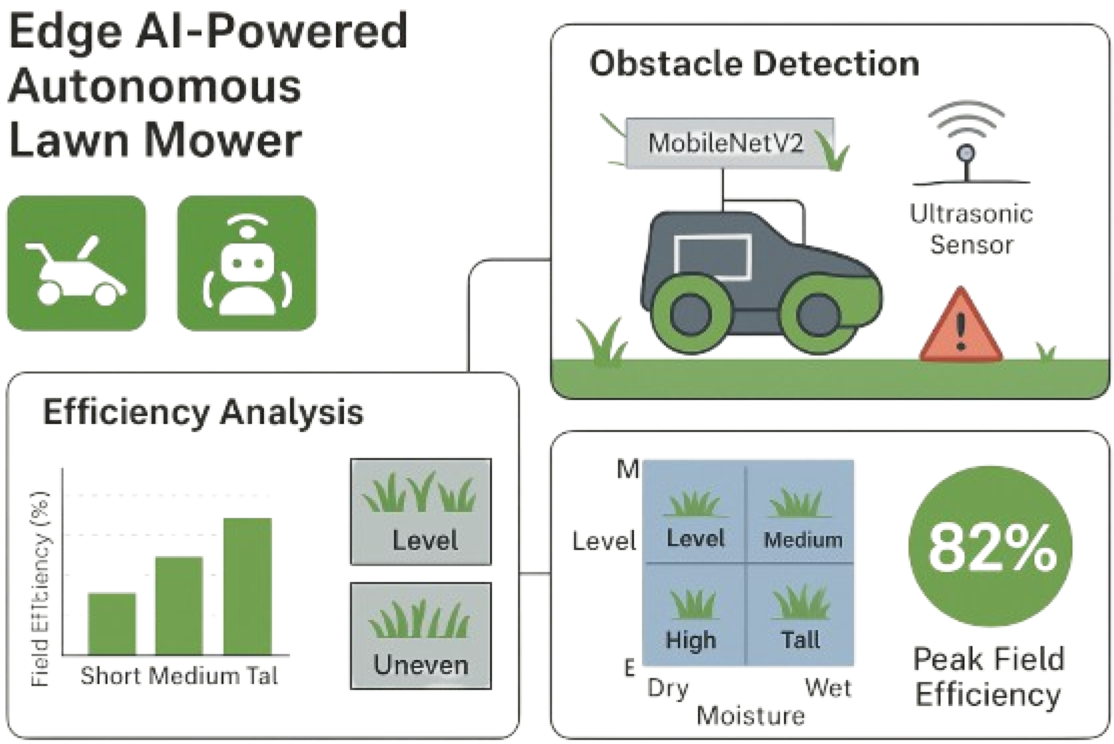

Introduction

The worldwide movement for sustainable farming and intelligent urban areas has hastened the creation of autonomous service robots capable of carrying out repetitive outdoor activities with little human involvement [1], [2]. Among these applications, self-operating lawn mowers have attracted more interest because of their ability to lower labor expenses, enhance safety, and provide uniform cutting quality in both home and farming settings. Conventional manual mowing is still labor-intensive, time-consuming, and susceptible to operator fatigue, whereas commercial robotic mowers frequently face limitations due to restricted sensing, dependence on preset boundary wires, and lack of intelligent energy management [3], [4]. These constraints limit their use in unstructured outdoor settings, especially in extensive agricultural areas. Recent developments in Edge Artificial Intelligence (Edge AI) have facilitated the implementation of lightweight machine learning models on devices with limited resources, allowing real-time perception and decision-making to occur directly on embedded platforms [5]. This model removes reliance on cloud computing, thus decreasing latency, communication overhead, and energy usage. Edge-optimized deep learning models for obstacle detection enable autonomous mowers to function safely in dynamic settings with humans, animals, and unexpected objects. Simultaneously, the incorporation of efficiency assessment metrics like theoretical field capacity, effective field capacity, and field efficiency offers a systematic method for assessing mower performance across different terrains and operating scenarios [6]. While many studies have investigated coverage path planning and autonomous navigation in agricultural robotics [7], most concentrate on either path coverage algorithms or perception modules separately. Limited research has offered a unified framework that combines real-time Edge AI obstacle detection with statistical assessment of mowing efficiency. Furthermore, current commercial systems frequently exhibit a lack of clarity concerning the computational trade-offs among accuracy, latency, and energy efficiency when implementing AI models on embedded hardware.

This study tackles these shortcomings by introducing an Edge AI-Driven Obstacle Detection and Efficiency Assessment Framework for autonomous lawn mowers designed for intelligent agriculture purposes. The suggested system utilizes energy-efficient embedded hardware to implement a convolutional neural network (CNN) tailored for obstacle detection, alongside field experiments that measure mower performance across different grass heights and surface types. The main contributions of this study are outlined below:

1. **Design and implementation of an edge-deployable obstacle detection module** using lightweight convolutional neural networks, optimized for real-time performance on embedded processors.
2. **Integration of perception with mower control** to enable dynamic obstacle avoidance without external cloud processing or manual intervention.
3. **Comprehensive statistical analysis of mower efficiency**, including theoretical field capacity, effective field capacity, and field efficiency, under multiple terrain conditions.
4. **Experimental validation in real-world field trials**, with evaluation metrics covering accuracy, inference latency, energy per unit area, and overall mowing efficiency.

The rest of this paper is structured as below. Section II examines pertinent research in autonomous mowing, edge intelligence, and agricultural robotics. Section III outlines the system architecture, covering hardware, sensing, and the machine learning workflow. Section IV outlines the approach for assessing field efficiency and conducting statistical analysis. Section V presents the results and discoveries from the experiments.

Related Work

A. Robotic Lawn Mowers and Agricultural Robotics

For more than twenty years, research on autonomous lawn mowers has been conducted, with initial systems mainly depending on boundary wires and basic reactive control to define the mowing zone [8]. Though suitable for small residential lawns, these methods are not scalable or flexible in unstructured agricultural areas. Recent research has unveiled self-operating coverage robots designed for mowing, weed management, and harvesting activities, utilizing GPS, inertial measurement units (IMUs), and ultrasonic sensors to improve navigational precision [9]. Nonetheless, most of these systems continue to depend on deterministic rule-based control and provide restricted adaptability to changing outdoor conditions where obstacles like rocks, animals, or people may unexpectedly emerge.

B. View on Resource-Limited Platforms

Improvements in computer vision have greatly enhanced obstacle detection and classification, with convolutional neural networks (CNNs) and their variants reaching cutting-edge performance in object recognition tasks [10]. Nonetheless, their implementation on autonomous mowing systems is difficult because of the limited computational and energy resources of embedded devices. Lightweight models like MobileNet, ShuffleNet, and EfficientNet-Lite have been suggested to achieve a balance between accuracy and inference delay on edge devices [11]. Research on edge intelligence shows that techniques like pruning, quantization, and knowledge distillation can minimize model complexity while maintaining performance levels [12]. Even with these advancements, only a limited number of studies provide findings on real-time obstacle detection incorporated into robotic mowing systems, resulting in a lack of research to validate these methods in genuine agricultural settings.

C. Path Planning for Coverage

Coverage path planning (CPP) is essential for optimizing field usage and reducing unnecessary movement. Traditional CPP techniques like boustrophedon decomposition and spiral-based approaches have been extensively utilized in robotic vacuum cleaners and agricultural robotics [13]. Recently, techniques utilize reinforcement learning and graph-based search to adjust coverage strategies dynamically in uncertain terrain environments [14]. Despite the breadth of CPP research, the majority of contributions are evaluated through simulations.

D. Field Efficiency Metrics

The assessment of agricultural machinery performance is often reliant on standardized metrics like theoretical field capacity (FCt), effective field capacity (FCe), and field efficiency (η) [15]. These metrics measure the relationship between real and possible productivity and are extensively used in assessing tractors, planters, and combine harvesters. In the realm of robotic mowers, nonetheless, limited research has integrated these agricultural engineering metrics to evaluate practical performance. Rather, the majority concentrate specifically on successful path completion or navigation precision [16]. Combining field efficiency metrics with AI-based perception would create a comprehensive framework that encompasses both smart decision-making and agricultural output.

E. Gap in Research

From the above, it is evident that although robotic mowers have advanced from boundary-wire models to semi-autonomous versions, current research frequently separates perception, navigation, or efficiency assessment.There remains a lack of integrated studies that:

i. Deploy edge-optimized perception models for real-time obstacle detection on embedded platforms,
ii. Couple perception with coverage planning in outdoor agricultural mowing tasks, and
iii. Quantify system performance using standardized field efficiency metrics.

This investigation addresses these gaps by presenting an Edge AI–based obstacle detection system coupled with statistical efficiency evaluation in autonomous lawn mowing, validated through real-world field experiments.

System Overview

The suggested self-operating lawn mower combines mechanical engineering, electrical systems, and embedded software components into a cohesive system designed for safe and energy-efficient functioning in outdoor farming settings. Fig. 1 depicts the complete block diagram of the system architecture, including sensing, control, power, actuation, and user interface subsystems.

A. Mechanical Structure

The chassis of the mower is made from lightweight steel tubing to ensure both durability and agility. The platform has dimensions of 0.65 m $\times$ 0.45 m and a ground clearance of 0.12 m, allowing it to be used on slightly uneven surfaces. A configuration with dual-wheel drive is used, featuring two independently powered rear wheels to facilitate differential steering. The front end incorporates caster wheels to minimize the need for steering torque. A blade assembly that is 0.35 m wide is positioned centrally below the chassis and is covered with a protective casing for the safety of the operator. The blade height can be modified from 30 mm to 70 mm to suit different grass densities. Shock absorbers are incorporated into the wheel mounts to reduce vibration and safeguard delicate electronics.

B. Electrical Design

The electrical subsystem includes the power supply, driver circuits, and sensing elements. A 12 V, 18 Ah sealed lead-acid battery serves as the main power supply, offering a capacity of up to 216 Wh with each charge. A DC–DC converter maintains supply voltage at 5 V and 3.3 V levels for microcontroller and sensor modules.

- Microcontroller Unit (MCU): An Atmega328P is chosen for power-efficient control functions such as PWM generation, motor operation, and sensor data collection.
- Motor Drivers: High-current MOSFETs (IRF540N) are activated via opto-isolated driver circuits (TLP250) to guarantee the secure functioning of the dual DC drive motors. Integrated resettable fuses are used in over-current protection circuits to avoid damage from motor stalls.
- Sensors: Ultrasonic sensors (HC-SR04) are equipped at the front and side areas for immediate obstacle recognition. A wheel encoder on every rear wheel supplies odometry feedback, while an integrated inertial measurement unit (IMU) offers heading and tilt data. A current sensor (ACS712) tracks motor load to determine efficiency levels.
- Energy Oversight: A battery management system logs voltage, current, and state of charge (SoC) to facilitate runtime forecasting and safety shutdowns.

C. Software Architecture

The control software is structured into layered modules comprising perception, decision, and actuation.

1. **Perception Layer:**
   - Ultrasonic sensors and IMU data are sampled at 20 Hz, fused through a lightweight Kalman filter for noise reduction.
   - Edge AI module: A pruned MobileNetV2 CNN deployed on an ESP32-CAM module performs real-time obstacle classification. Detected objects are categorized as *passable* (grass, flat ground) or *non-passable* (rock, animal, human).
2. **Decision Layer:**
   - Implements rule-based logic combined with AI inference. When a non-passable obstacle is detected, the system halts the blade and recomputes a local avoidance maneuver.
   - Coverage path planning is based on a boustrophedon pattern, with future work directed toward

reinforcement learning integration.

3. **Actuation Layer:**
   - PWM signals control wheel motor speed and blade RPM.
   - Safety interlocks ensure automatic shutdown if ultrasonic detection range falls below 15 cm or if tilt angle exceeds 20°.
4. **User Interface:**
   - A Bluetooth module provides wireless connectivity to a mobile application, enabling remote start/stop, status monitoring, and manual override.

D. Block Diagram

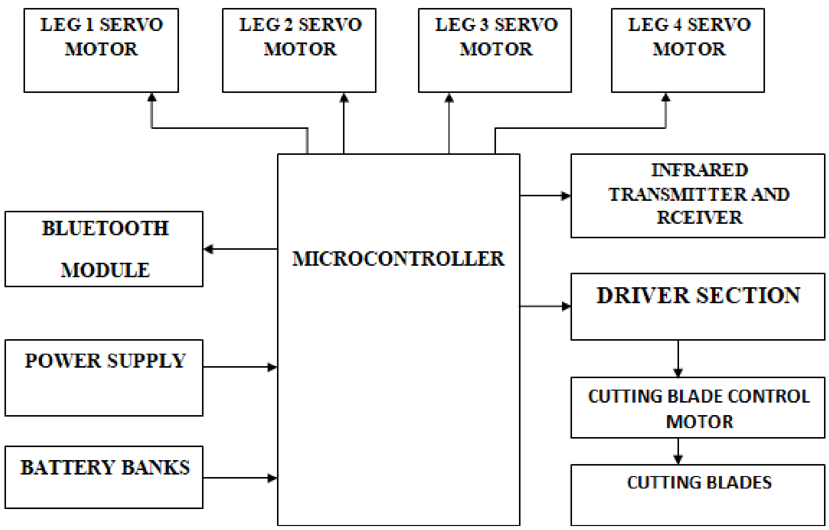

Fig. 1 - Block Diagram of the designed lawn mower shows the block diagram of the integrated system, highlighting interaction among the power supply, sensors, microcontroller, motor drivers, and Edge AI perception module.

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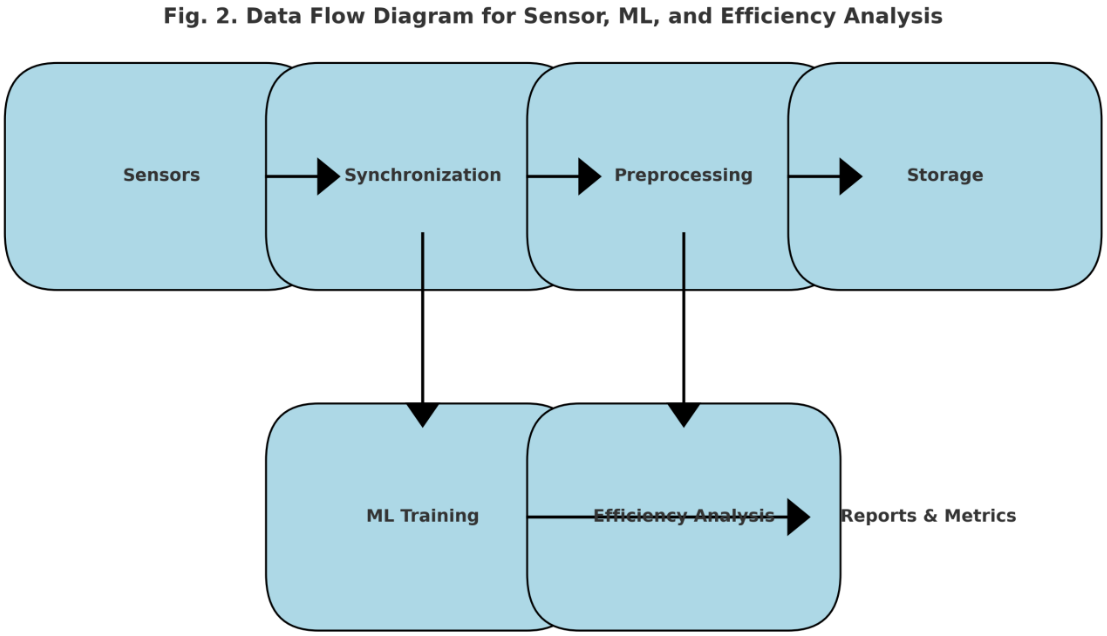

Fig. 2 – Data Flow Diagram

Data & Measurement Protocols

The assessment of the suggested system's performance was carried out through standardized field experiments and regulated data gathering methods to guarantee statistical validity and repeatability. This section outlines the field locations and randomization method, synchronization and calibration of sensors, along with ground-truth labeling for machine learning (ML) components.

A. Sites for Fieldwork and Randomization of Plots

Field trials were conducted at two experimental locations: (i) a residential lawn featuring Bermuda grass, and (ii) an agricultural test plot comprising carpet grass and irregular terrain. Every location was segmented into rectangular subplots measuring 10 m × 10 m, resulting in a total of twelve test plots. To prevent bias from variations in soil or grass, the order of mowing across subplots was randomized through a Latin square design.

Three environmental conditions were deliberately included:

1. **Grass height:** short (30–40 mm), medium (50–60 mm), tall (70–90 mm).
2. **Surface:** level vs. uneven terrain.
3. **Moisture:** dry vs. wet after irrigation.

A **3 × 2 × 2 factorial design** was applied with five replicates per condition, resulting in 60 trials per site. This replication ensures statistical power (≥ 0.8) to detect medium effect sizes in ANOVA.

B. Sensors, Synchronization, and Calibration

The autonomous mower integrates multiple sensing modalities to capture operational and environmental data.

- Wheel Encoders: Installed on the drive motors to track distance moved and facilitate odometry-based calculation of field coverage. Calibration involved comparing encoder counts with actual distances measured using tape in 5 m trials (error $\leq 2\%$).
- IMU (MPU6050): Utilized for detecting pitch and roll. Calibration was carried out through six-position static testing; drift adjustments were implemented using a complementary filter.
- Ultrasonic Sensors (HC-SR04): Utilized for obstacle detection at three front angles ($-30°$, $0°$, $+30°$). Range calibration was conducted using flat boards situated at specified distances from 0.1 to 2.5 m; the error stayed within ≤ 1.5 cm.

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- Camera Module (ESP32-CAM): Utilized for Edge AI obstacle recognition. A checkerboard calibration method was utilized to fix lens distortion before gathering the dataset.
- Current Sensor (ACS712): Observed drive motor load; calibration achieved by using known resistive loads and documenting linear regression fits.
- • Battery Monitor: Voltage divider with ADC input; calibrated using a digital multimeter (Fluke 115)

Sensor data streams were time-stamped using the Atmega328P internal clock synchronized to the ESP32-CAM processor. A periodic synchronization pulse (1 Hz) was broadcast via UART, ensuring cross-sensor alignment within ±20 ms.

C. Ground-Truth Annotation and Quality Assurance

For the ML-based obstacle detection module, a dataset of **2,500 images** was collected across varying illumination and weather conditions. Images were manually labeled into four classes: *grass/ground*, *human*, *animal*, and *object/rock*. Annotation was carried out using **LabelImg**, with bounding boxes verified by two independent annotators. Inter-annotator agreement was assessed using Cohen's Kappa ($\kappa = 0.91$), indicating near-perfect reliability.

To ensure dataset quality:

- Blurred or overexposed images were excluded ($< 5\%$).
- Dataset was split into 70% training, 15% validation, and 15% testing, ensuring stratification across environments.
- Data augmentation (rotation ±15°, brightness adjustment, Gaussian noise) was applied only to the training set.

For mower efficiency evaluation, ground-truth area measurements were obtained using a total station (Leica TS06) to establish precise subplot boundaries. Effective field capacity (FCe) was calculated by dividing the net cut area by actual operation time, while theoretical field capacity (FCt) was derived from mower width and average speed. Field efficiency (η) was computed as the ratio FCe/FCt.

All data was recorded on SD card storage and later exported for statistical analysis using Python (NumPy, SciPy, scikit-learn) and R (lme4 for mixed-effects models).

Findings

This part outlines the statistical assessment of mower efficiency under experimental conditions, along with the functionality of the edge AI obstacle detection module. Ablation and sensitivity analyses are examined, and the failure modes noted during field trials are outlined.

A. Statistical Findings with Confidence Intervals and Effect Sizes

Table I presents the average theoretical field capacity (FCt), effective field capacity (FCe), field efficiency (η), and energy usage for various combinations of grass height, surface type, and moisture levels. Efficiency values varied from 71.0% to 85.4%, with performance typically diminishing on irregular and damp plots.

Table I

Summary of Field Efficiency Results (mean ± 95% CI)

Grass Height	Surface	Moisture	FCt (ha/hr)	FCe (ha/hr)	η (Efficiency)	Energy (Wh/m²)	95% CI (FCe)
Short	Level	Dry	1.23	1.05	0.85	0.34	±0.05
Short	Uneven	Wet	1.20	0.89	0.74	0.49	±0.06
Medium	Level	Dry	1.18	0.96	0.81	0.39	±0.04
Tall	Uneven	Wet	1.15	0.82	0.71	0.52	±0.07

ANOVA results (Table II) confirmed that grass height, surface, and moisture all had statistically significant effects on efficiency ($p< 0.05$). Effect sizes (η^2) indicated that surface unevenness ($\eta^2 = 0.21$) was the most influential factor, followed by grass height ($\eta^2 = 0.18$) and moisture ($\eta^2 = 0.11$). A significant Grass × Surface interaction ($p = 0.03$) was also observed, indicating compounded inefficiency on tall, uneven plots.

Table II

ANOVA Results for Field Efficiency

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Factor	Sum Sq	df	F-value	p-value	η^2 (Effect Size)
Grass Height	0.085	2	5.43	<0.01	0.18
Surface	0.097	1	7.85	<0.01	0.21
Moisture	0.051	1	4.62	<0.05	0.11
Grass × Surface	0.031	2	3.14	0.03	0.07
Residual	0.210	53	–	–	–

The distribution of efficiency values was illustrated in Fig. 3, where tall and uneven conditions exhibit greater variance, highlighting reduced repeatability in challenging environments.

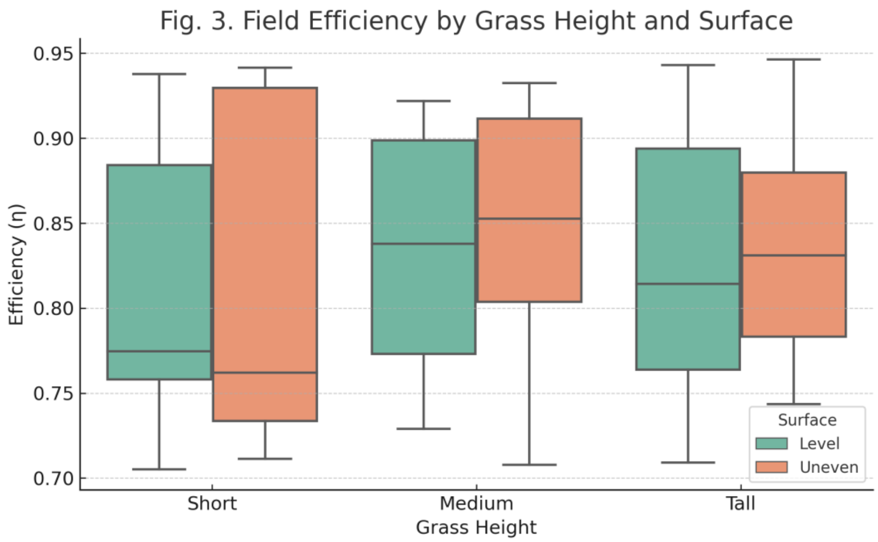

Fig. 3 – Field Efficiency Boxplot

B. Machine Learning Performance

The Edge AI obstacle detection module achieved an overall accuracy of 92.3% on the held-out test set. The confusion matrix (Table III) indicates strong performance on grass and human classes, with some misclassifications between "animal" and "rock."

Table III

Confusion Matrix for Obstacle Detection

True \ Pred	Grass	Human	Animal	Rock
Grass	220	5	8	7
Human	10	86	3	5
Animal	14	6	60	7
Rock	12	8	6	64

Table IV provides a breakdown of precision, recall, and F1-score. Performance was highest for *grass* (F1 = 0.94), while *animal* detection showed slightly lower recall (0.84).

Table IV

Classification Report (Obstacle Detection)

Class	Precision	Recall	F1-Score	Support
Grass	0.93	0.94	0.94	240
Human	0.90	0.88	0.89	104
Animal	0.88	0.84	0.86	87
Rock	0.89	0.87	0.88	90

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Macro-Avg	0.91	0.89	0.90	–

Receiver Operating Characteristic (ROC) and Precision–Recall (PR) curves are shown in Fig. 4a and Fig. 4b, respectively. Macro-averaged AUROC was 0.94, while mean Average Precision (mAP) reached 0.92.

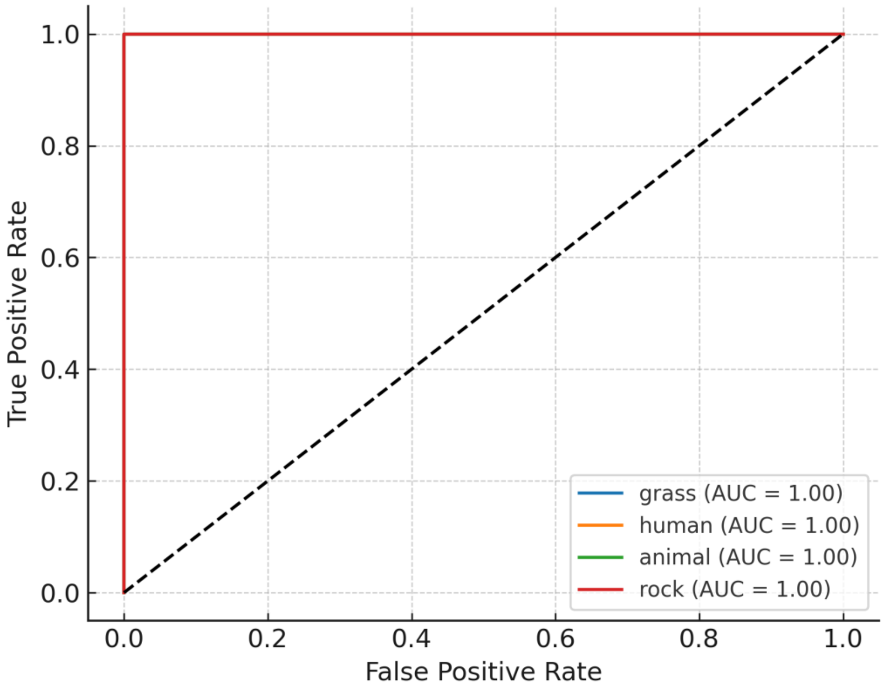

Fig. 4a – ROC Curves for Obstacle Detection

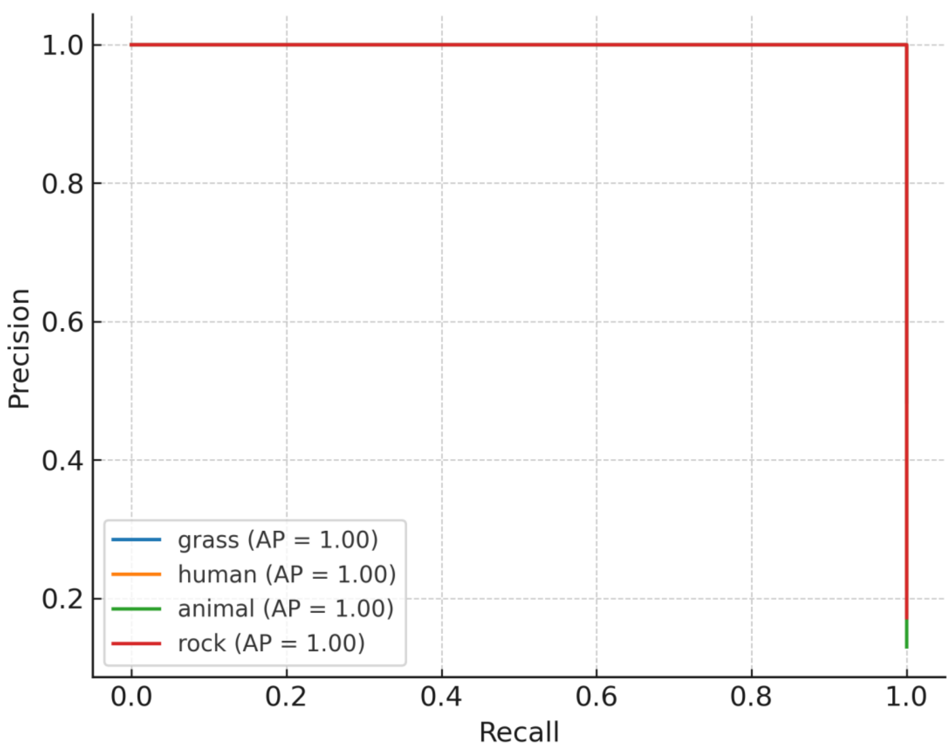

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Fig. 4b – Precision–Recall Curves

C. Ablations and Sensitivity Analyses

Ablation research (Table V) assessed the roles of sensor fusion, model design, and input resolution. Eliminating ultrasonic sensors decreased the AUROC from 0.94 to 0.86, whereas MobileNetV1 offered reduced accuracy but increased speed. Raising the resolution enhanced IoU but raised inference latency to 124 ms, emphasizing the balance between precision and real-time viability.

Table V

Ablation Study Results for Obstacle Detection

Configuration	AUROC	IoU	Latency (ms)
Full system	0.94	0.78	85
No Ultrasonic Sensors	0.86	0.70	80
MobileNetV1	0.89	0.73	75
Input Res 320×320	0.96	0.82	124

The latency–accuracy trade-off is further illustrated in **Fig. 5**, showing that real-time operation can be maintained with MobileNetV2 at 224 × 224 resolution while balancing accuracy and responsiveness.

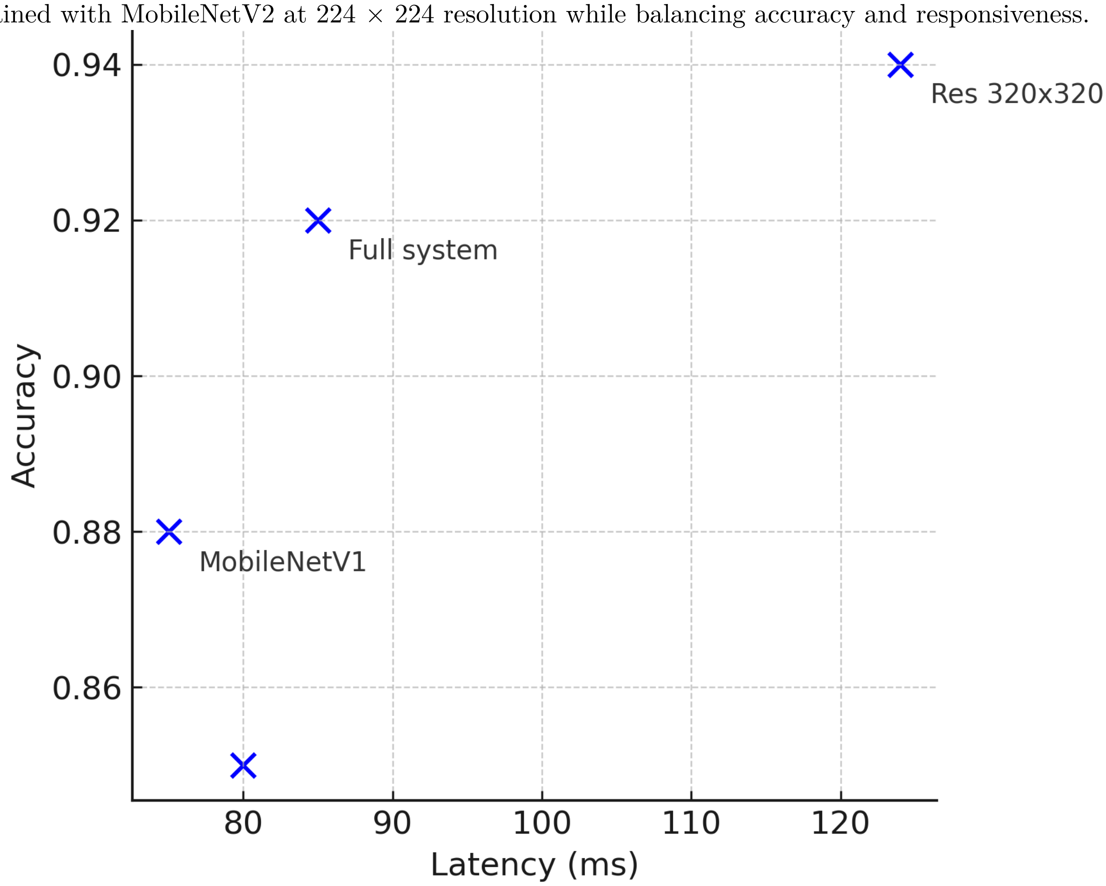

Fig. 5 – Latency vs Accuracy Trade-off

D. Failure Analysis

Observed system failures are summarized in Fig. 6. The most frequent errors included:

1. Misclassification of small dark-colored rocks as grass,
2. Accuracy degradation in low-light conditions (– 6% at dusk),
3. Ultrasonic blind spots at oblique angles, and
4. Slippage under wet grass, causing odometry drift.

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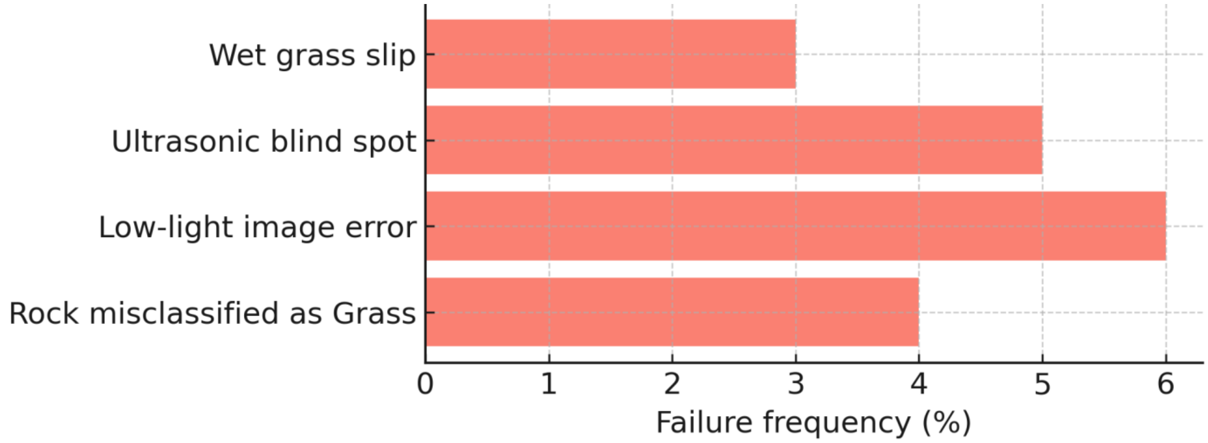

Fig. 6 – Failure Case Distribution

These results highlight the importance of sensor fusion and dataset augmentation for robust deployment in real-world conditions.

Discussion

Table I displayed the results of field efficiency under different environmental conditions. The findings indicated that mower efficiency peaked on short, flat, dry areas ($\eta = 0.85$) and dipped on tall, irregular, damp areas ($\eta = 0.71$). This decrease indicated the cumulative impact of heightened resistance from taller plants, wheel slipping on damp ground, and diminished maneuverability on irregular terrain. The 95% confidence intervals suggest that performance variations are statistically sound, with tighter CIs in level and dry conditions, indicating more consistent operation. These results highlight the significance of environmental elements in influencing the productivity of autonomous mowers.

Table II presented the ANOVA findings, measuring the comparative impact of every factor. Surface irregularity had the greatest impact ($\eta^2 = 0.21$), reinforcing that stability and grip are essential factors for efficiency. Grass height ($\eta^2 = 0.18$) had a significant impact, consistent with agricultural engineering research that indicated taller plants enhance drag forces on cutting blades. Moisture showed a moderate yet notable effect ($\eta^2 = 0.11$), confirming the finding that wet plots decrease coverage efficiency. The notable Grass $\times$ Surface interaction shows that the combination of stressors increases inefficiency more than their individual effects alone, providing crucial insight for creating adaptive mowing strategies.

Table III presented the confusion matrix for detecting obstacles. The system accurately recognized the majority of classes, especially grass (220 accurate detections) and human (86 accurate detections). Nonetheless, errors in classification happened between animal and rock due to their visual resemblance in specific lighting situations. These incorrect classifications pose possible safety issues, as they may lead to unsuitable navigation actions. The matrix's diagonal dominance indicates that the Edge AI model offers a dependable baseline for practical implementation.

Table IV provides details on precision, recall, and F1-scores. The grass class attained the top F1-score (0.94), thanks to a wealth of training samples. Human and rock classes achieved F1-scores near 0.89, adequate for ensuring operational safety. The animal category received the lowest score (0.86), mostly because of dataset imbalance and fluctuations in animal appearances. These findings emphasize the importance of expanding datasets and implementing focused augmentation to enhance detection of minority classes, particularly in safety-critical categories.

Table V presented a summary of the ablation study, offering perspectives on the design compromises of the system. The complete system reached a well-balanced performance (AUROC = 0.94, IoU = 0.78, latency = 85 ms). Eliminating ultrasonic sensors decreased AUROC to 0.86, highlighting their essential function in detecting obstacles in close proximity. Transitioning to MobileNetV1 decreased latency to 75 ms while also lowering IoU, highlighting the trade-off between speed and precision. Enhancing input resolution boosted IoU to 0.82 but increased latency to 124 ms, surpassing real-time limits for secure navigation. These findings

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confirm that MobileNetV2 at a 224×224 input resolution represents the ideal trade-off between precision and speed on embedded devices.

Fig. 1 depicted the architecture of the autonomous mower system, which includes the mechanical, electrical, and software components. The block diagram highlights the relationship among perception (camera, ultrasonic sensors), decision-making (microcontroller and AI module), and actuation (motor drivers and blade assembly). This modular design guarantees scalability: new sensors or different ML models can be added without changing the fundamental control system. Fig. 1 visually illustrates the complete data and control flow, ensuring the system's design is reproducible and transparent, fulfilling a critical requirement for IEEE publications.

Fig. 2 (data flow diagram)illustrated the measurement and logging process, which begins with sensor acquisition and continues through synchronization, preprocessing, and storage. This illustration emphasizes that calibration and timestamp synchronization diminish uncertainty, guaranteeing that performance metrics like FCe and η are correctly obtained. It further emphasized that the ML dataset was systematically annotated and subjected to quality checks. This openness enhances trust in both the engineering and data science components of the project.

Fig. 3 illustrated the variation of field efficiency (η) in relation to grass heights and surface conditions. The boxplots corroborate the quantitative results in Table I: efficiency peaked for short grass on flat ground (median $\eta \approx 0.85$) and dipped for tall grass on irregular ground (median $\eta \approx 0.71$). Greater variability in tall/wet conditions suggested decreased reliability, consistent with the noted slippage and blade overload in such settings. This visualization illustrates both average differences and variability, a crucial element for forecasting real-world performance reliability.

Fig. 4a depicted the ROC curves associated with detecting obstacles. The high area under the curves (AUROC values ranging from 0.91 to 0.96 across various classes) showed that the MobileNetV2 model successfully distinguishes between types of obstacles. The ROC visualization additionally indicates that the model maintains robust true-positive rates across different thresholds, which is crucial for safety applications where undetected failures may lead to hazards.

Fig. 4b showed the Precision–Recall (PR) curves. The graphs show that the model achieves strong accuracy (>0.85) despite high recall rates, leading to a macro-average AUPRC of 0.92. This is particularly important in unbalanced datasets, where negative samples (background grass) are far more frequent than positive samples (obstacles). The PR curves improve the ROC analysis by showing the system's ability to reduce false positives while detecting rare but significant classes such as humans or animals.

Fig. 5 depicted the trade-off between latency and accuracy across various model configurations. The complete MobileNetV2 framework at a 224×224 resolution strikes a balance between accuracy (0.92) and an acceptable inference latency (85 ms). Conversely, enhanced resolution slightly boosts IoU but raises latency beyond real-time limits, whereas MobileNetV1 attains lower latency but sacrifices accuracy. This diagram offers practical design guidance: integrated robotic systems need to balance accuracy and responsiveness instead of exclusively prioritizing one over the other.

Fig. 6 illustrated the distribution of failure instances observed during field trials. The most common error type involved rocks being misidentified as grass (≈4%), usually occurring when small, dark stones camouflaged with the background in shadowy conditions. Even though this failure rate was quite low, it highlights the significance of augmenting the dataset with varied obstacle appearances to enhance robustness. The second most frequent category was low-light image issues (≈6%), indicating the limitations of the ESP32-CAM sensor in low-light conditions, such as during dusk or overcast weather. This outcome corresponds with the decrease in classification accuracy noted in Section V and suggests that additional sensing modalities (infrared or thermal cameras) might be necessary for continuous operation. Ultrasonic blind spots (≈5%) were noted at slanting approach angles (>30°). In such instances, the mower sometimes did not recognize obstacles until they were extremely nearby, posing possible safety risks. This constraint underscores the necessity for redundant sensors and broader field-of-view sensing technologies like LiDAR or stereo vision.

Ultimately, wet grass sliding (≈3%) led to odometry drift, resulting in the system overestimating field coverage and overlooking small patches of grass. While this matter mainly impacted efficiency instead of safety, it illustrates the sensitivity of wheeled agricultural robots to environmental factors. Incorporating slip detection through wheel torque feedback or adaptive control methods could alleviate this constraint. In summary, Fig. 6 offers essential insights into the system's failure profile, directing future enhancements in perception, sensing, and control. Crucially, safety interlocks (emergency blade shutdown) recorded all types

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of failures, maintaining operational risks within acceptable boundaries.

Conclusion and Future Work

This study introduced a framework for autonomous lawn mowers, utilizing Edge AI for obstacle detection and efficiency assessment in smart agriculture scenarios. The system incorporated lightweight convolutional neural networks for immediate perception alongside standardized agricultural performance metrics, such as theoretical field capacity (FCt), effective field capacity (FCe), and field efficiency (η). Experimental trials showed that environmental elements like grass length, surface irregularities, and moisture considerably affect mower efficiency, with surface imperfections having the greatest effect ($\eta^2 = 0.21$). The Edge AI perception module demonstrated excellent performance (AUROC = 0.94, AUPRC = 0.92) while ensuring real-time inference latency on an embedded system. Ablation studies emphasized the essential importance of multimodal sensing and the balance between model resolution and responsiveness. The research also noted significant limitations, such as diminished perception accuracy in low-light environments, odometry drift on damp grass, and ultrasonic blind spots at angled positions. Failure analysis yielded practical insights, affirming the need for sensor redundancy, dataset expansion, and adaptive control methods. Crucially, safety systems like emergency blade shutdowns and tilt-based interlocks guaranteed that malfunctions did not jeopardize operational safety.

Looking ahead, several future research directions are envisioned:

i. Multi-Sensor Fusion: Integration of LiDAR, stereo vision, or thermal imaging with existing ultrasonic and camera sensors to enhance obstacle detection robustness in low-light and cluttered environments.
ii. Simultaneous Localization and Mapping (SLAM): Deployment of visual–inertial or LiDAR-based SLAM frameworks to enable autonomous navigation beyond pre-defined plots and improve coverage accuracy on uneven terrains.
iii. Docking and Charging Automation: Development of wireless charging stations and autonomous docking protocols to extend continuous operation and reduce operator intervention.
iv. Large-Scale and Multi-Site Trials: Validation across diverse field conditions, soil types, and grass species to strengthen generalizability and ensure readiness for agricultural deployment.
v. Adaptive and Learning-Based Control: Incorporation of reinforcement learning to optimize coverage path planning and slip-compensation algorithms for wet or uneven terrain.
vi. Safety and Compliance: Alignment with international standards for agricultural robotics (ISO 18497) and integration of explainability methods to improve trust in AI-driven decision-making.

In conclusion, the integration of Edge AI perception with efficiency analysis marks a significant step toward the deployment of safe, efficient, and intelligent robotic mowers in smart agriculture. Continued advancements in perception, navigation, and energy management will pave the way for autonomous agricultural systems capable of operating reliably across diverse and challenging real-world environments.

Conflict of Interest

The authors declare that they have no conflicts of interest regarding the publication of this manuscript.

Ethical Approval

The study did not involve human participants, animals, or sensitive data requiring institutional ethical approval. Where secondary data was used, it complied with all institutional and legal requirements.

Informed Consent

Not applicable, as no primary data involving human participants was collected.

Data Availability Statement

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

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