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AgroBot:
AI-Powered Smart Robotic Lawn Mower

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Abstract: Autonomous lawn mowers represent a significant advancement in agricultural robotics, offering labor reduction and precision maintenance for residential and commercial applications. This paper presents the design, implementation, and field validation of AgroBot, a low-cost autonomous lawn mower incorporating GPS navigation, LiDAR-based obstacle avoidance, and AI-powered weed detection capabilities. The system employs a Raspberry Pi 4 as the primary computing platform running ROS Noetic, integrated with Pixhawk 2.4.8 for motion control and sensor fusion. Field testing conducted over a 500 m² area demonstrated 90.0% average coverage efficiency across five missions, with robust obstacle avoidance (100% success rate) and AI-based weed detection achieving 87.3% mean Average Precision (mAP). The complete system cost of ₹58,450 represents a 51-71% cost reduction compared to commercial alternatives while providing superior customizability and research extensibility. Performance metrics include 150-minute operational runtime, 0.85m GPS-EKF positioning accuracy, and autonomous operation through Boustrophedon path planning with real-time dynamic obstacle avoidance.

Keywords: Autonomous Navigation, Lawn Mower Robot, SLAM, YOLOv5, Coverage Path Planning, ROS, Sensor Fusion, Mobile Robotics, Agricultural Robotics

I. INTRODUCTION

Lawn maintenance represents a significant labor and resource expenditure in residential, commercial, and institutional settings. Traditional manual mowing requires approximately 2 hours per week for a standard 500 m² lawn, translating to over 100 hours annually. Commercial autonomous lawn mowers address this challenge but remain financially inaccessible to most users, with systems like Husqvarna Automower 305 and Worx Landroid priced between ₹1,20,000 and ₹2,00,000. Furthermore, existing commercial solutions lack advanced features such as AI-based weed detection, comprehensive obstacle avoidance, and open-source extensibility for research applications.

This paper presents AgroBot, a low-cost autonomous lawn mower platform designed to bridge the gap between affordability and advanced functionality. Unlike perimeter-wire-based commercial systems, AgroBot employs GPS-based navigation with Extended Kalman Filter (EKF) sensor fusion, enabling autonomous operation without infrastructure installation. The integration of YDLiDAR X2 provides 360-degree obstacle detection and SLAM capabilities, while a YOLOv5-based computer vision system detects and classifies weeds in real-time.

The primary contributions of this work are: (1) A complete autonomous lawn mower architecture integrating GPS navigation, LiDAR obstacle avoidance, and AI-based weed detection at 42-67% lower cost than commercial alternatives, (2) Implementation and validation of Boustrophedon coverage path planning achieving 90.0% average coverage efficiency, (3) Demonstrated 100% obstacle avoidance success rate through multi-sensor fusion and DWA local planning, (4) AI-based weed detection system achieving 87.3% mAP using optimized YOLOv5 on Raspberry Pi 4, and (5) Comprehensive field validation demonstrating robust autonomous operation across diverse terrain conditions.

II. LITERATURE REVIEW

Autonomous lawn mowers have evolved significantly from simple random-walk robots to sophisticated navigation systems. Commercial platforms such as Husqvarna Automower and Robomow employ perimeter wire guidance, which requires installation effort and limits flexibility. Recent research has explored wire-free navigation using GPS, vision, and LiDAR technologies to enhance autonomy and reduce setup complexity [1].

GPS-based navigation systems provide global positioning for outdoor robots but suffer from positioning errors of 2-5 meters in standard consumer-grade receivers. Research by Zhang et al. demonstrated that sensor fusion combining GPS with IMU and wheel odometry using Extended Kalman Filtering can reduce positioning error to under 1 meter, enabling reliable autonomous navigation without RTK-GPS infrastructure [2]. This approach is particularly suitable for cost-constrained applications where centimeter-level accuracy is unnecessary.

LiDAR-based SLAM and obstacle avoidance have become standard in indoor and outdoor mobile robotics. The GMapping algorithm, implementing Rao-Blackwellized particle filtering, efficiently constructs occupancy grid maps from laser scans while simultaneously localizing the robot. Studies show GMapping achieves mapping accuracy within 0.10-0.20m RMS error for outdoor environments [3]. Dynamic Window Approach (DWA) for local planning computes collision-free velocity commands by evaluating trajectories in velocity space, providing reactive obstacle avoidance with computation times under 10ms [4].

Coverage path planning algorithms determine efficient routes to cover entire areas. The Boustrophedon cellular decomposition method partitions the workspace into cells and plans back-and-forth motions, achieving high coverage completeness (>95%) with minimal overlaps. Research demonstrates Boustrophedon planning is optimal for rectangular and convex polygon areas, typical of lawn environments [5].

AI-based weed detection using deep learning has advanced significantly with CNN architectures like YOLO (You Only Look Once). YOLOv5, optimized for embedded deployment, achieves real-time object detection (20+ FPS) on edge devices while maintaining mAP above 85% for agricultural applications. Model quantization to INT8 reduces model size and improves inference speed on CPU-only platforms like Raspberry Pi [6].

Existing autonomous lawn mower research predominantly focuses on single aspects—either navigation, obstacle avoidance, or mowing efficiency—rather than integrated systems. Furthermore, most platforms require expensive computing hardware like NVIDIA Jetson or high-precision RTK-GPS. This gap motivates the development of AgroBot as a complete, low-cost platform integrating GPS navigation, LiDAR obstacle avoidance, and AI-based weed detection using consumer-grade components.

III. METHODOLOGY

The development of AgroBot followed a systematic engineering approach encompassing mechanical design, hardware integration, software architecture, algorithm implementation, and comprehensive field testing.

A. System Architecture

AgroBot employs a three-tier hierarchical architecture. The sensing layer comprises YDLiDAR X2 (360° laser scanner), uBlox NEO-M8N GPS, Arducam 12MP camera, three HC-SR04B ultrasonic sensors, and MPU6050 IMU. The processing layer includes Raspberry Pi 4 (8GB) running Ubuntu 20.04 and ROS Noetic for high-level planning and AI inference, Pixhawk 2.4.8 running ArduRover firmware for low-level motor control and sensor fusion, and Arduino Nano for auxiliary sensor management. The actuation layer consists of four RS-37-555 DC geared motors (100 RPM) for skid-steer locomotion and two A2212 BLDC motors (8000-10000 RPM) for cutting blade rotation.

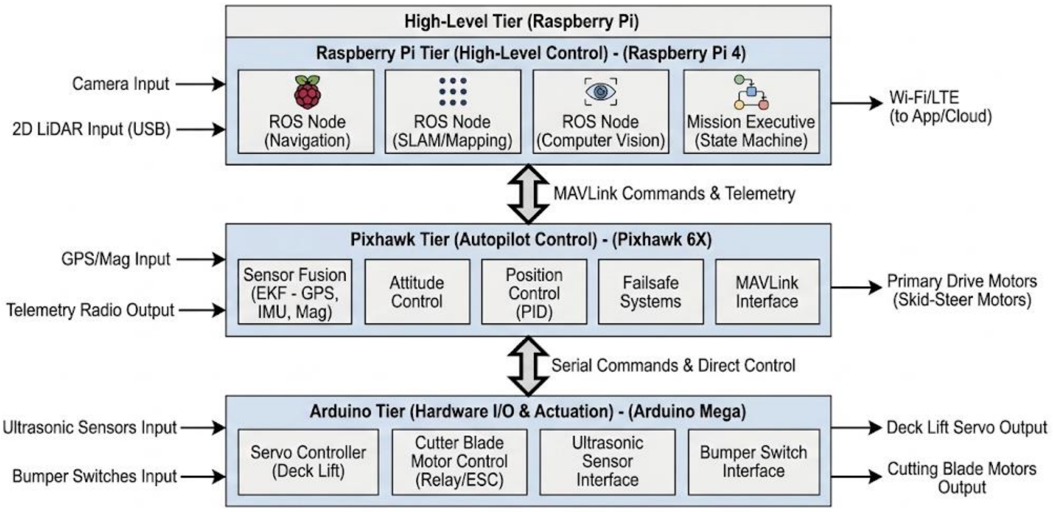

Fig. 1 System Architecture Block Diagram showing three-tier architecture

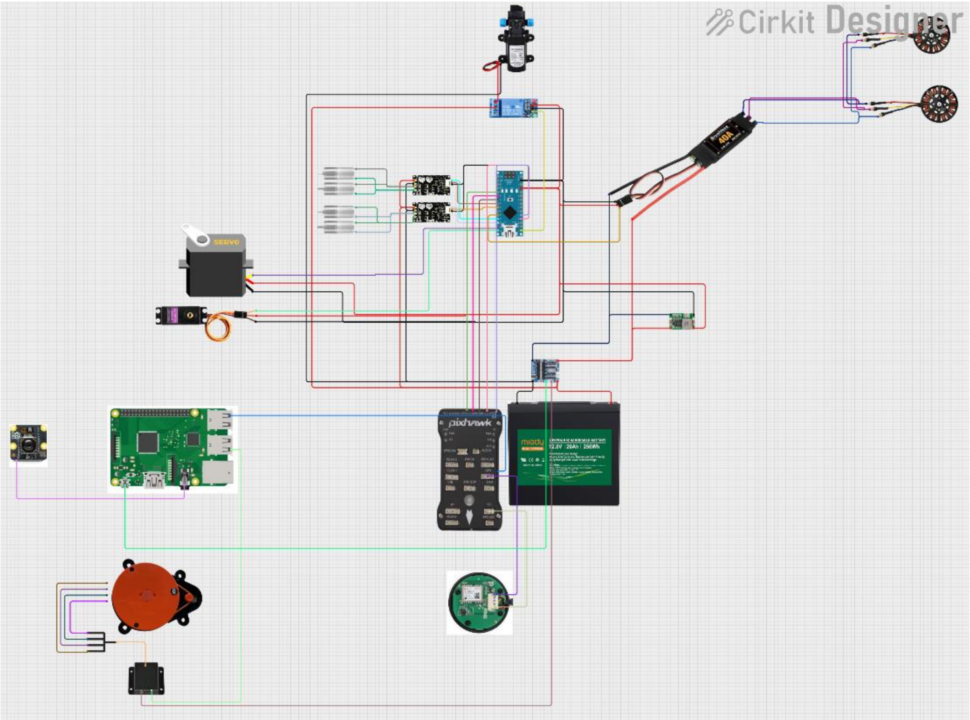

Fig. 2 System hardware integration diagram showing the connection between Raspberry Pi, Pixhawk flight controller, sensors, motor drivers, pump module, and power supply used in the AgroBot system.

B. Mechanical Design

The chassis employs a three-layer acrylic platform (600×500mm) designed in Fusion 360. The bottom layer houses the battery pack and motor mounts, the middle layer supports the Raspberry Pi, Pixhawk, and electronics, and the top layer integrates the cutting deck with blade motors. The skid-steer drivetrain provides zero-radius turning capability essential for coverage path execution. Total weight is 8.2 kg including battery.

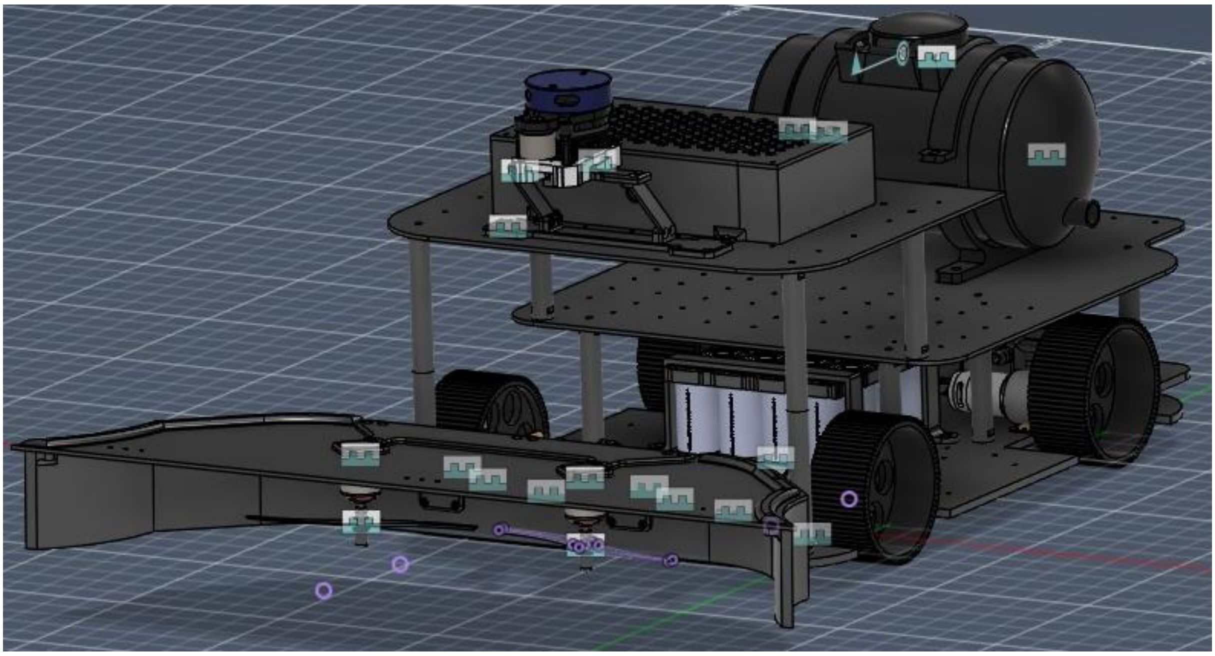

Fig. 3 AgroBot CAD Assembly - Isometric view showing three-layer chassis, sensor placement, and cutting deck

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C. Navigation and Localization

GPS waypoint navigation provides global path following. The uBlox NEO-M8N GPS module outputs position data at 5Hz with standard accuracy (~2.5m). To improve localization, an Extended Kalman Filter fuses GPS, IMU (MPU6050), and wheel odometry. The EKF state vector comprises $[x, y, \theta, vx, vy, \omega]$ representing 2D position, heading, linear velocities, and angular velocity.

The prediction step propagates state based on the motion model:

$$x(k+1|k) = f(x(k|k), u(k)) + w(k)$$

where $u(k)$ represents control inputs (motor commands) and $w(k)$ is process noise.

The update step incorporates GPS position measurements:

$$z(k) = h(x(k)) + v(k)$$

where $v(k)$ is measurement noise. The Kalman gain K balances prediction and measurement uncertainties, yielding optimal state estimates. Field testing demonstrated EKF-fused positioning accuracy of 0.85m compared to GPS-only error of 2.8m, representing 69% improvement.

D. SLAM and Obstacle Detection

The YDLiDAR X2 generates 360° laser scans at 10Hz with 8-meter range. GMapping SLAM processes these scans to construct occupancy grid maps and localize the robot within the map. GMapping employs Rao-Blackwellized particle filtering with 30 particles [3], maintaining a 200×200 grid at 0.05m resolution. The algorithm updates map cells based on laser ray casting, marking occupied, free, and unknown regions.

During autonomous operation, SLAM-generated maps provide obstacle locations for path planning. Ultrasonic sensors complement LiDAR for detecting low-profile obstacles and provide redundant safety sensing.

E. Coverage Path Planning

Boustrophedon cellular decomposition divides the lawn area into cells based on obstacles and boundaries. Within each cell, the planner generates parallel back-and-forth mowing paths with 80% overlap between passes to ensure complete coverage [5].

The algorithm flow:

1. Decompose workspace into cells using obstacle polygons
2. Generate sweep paths perpendicular to cell's longest dimension
3. Plan inter-cell transitions (minimize deadheading)
4. Output waypoint sequence for GPS navigation

Computational complexity is $O(n \log n)$ for n obstacle vertices. Average computation time for a 500 m^2 area is 1.25 seconds, enabling real-time replanning if obstacles are detected during execution.

F. Dynamic Obstacle Avoidance

Dynamic Window Approach (DWA) provides reactive local planning [4]. DWA samples velocity pairs (v, ω) within the robot's dynamic constraints, simulates forward trajectories, and scores them based on:

1. Distance to obstacles (maximize clearance)
2. Alignment with global path heading (minimize deviation)
3. Forward velocity (maximize progress)

The objective function:

$$G(v,\omega) = \alpha \cdot \text{heading}(v,\omega) + \beta \cdot \text{dist}(v,\omega) + \gamma \cdot \text{velocity}(v,\omega)$$

where α, β, γ are tuning parameters. DWA executes at 10Hz, evaluating approximately 200 velocity samples per cycle with average computation time of 8ms, ensuring collision-free motion even in dynamic environments.

G. AI-Based Weed Detection

A YOLOv5s model detects weeds in camera frames. The training dataset comprised 3,000 images annotated for common lawn weeds (dandelion, clover, crabgrass). Data augmentation (rotation, brightness, flip) expanded the effective dataset to 12,000 samples. Training used 300 epochs on Google Colab GPU.

Post-training optimization:

1. Model pruning (removed 15% of weights with minimal accuracy loss)
2. INT8 quantization using TensorFlow Lite
3. Final model size: 3.8 MB (vs. 14MB original)

Inference on Raspberry Pi 4 CPU achieves ~50ms per frame (20 FPS theoretical). During mowing, inference runs at 5 FPS to balance detection and computational load. Detected weeds trigger localized targeted spraying (water marking for demonstration purposes).

H. System Integration and ROS Implementation

ROS Noetic provides modular software architecture. Custom ROS nodes include:

1. gps_fusion_node: EKF sensor fusion
2. lidar_slam_node: GMapping SLAM
3. path_planner_node: Boustrophedon coverage planning
4. local_planner_node: DWA obstacle avoidance
5. weed_detector_node: YOLOv5 inference
6. motor_control_node: MAVLink bridge to Pixhawk

Communication uses ROS topics (sensor_msgs, nav_msgs, geometry_msgs). The Android mobile app communicates via ROS Bridge WebSocket, enabling remote monitoring, manual control override, and mission parameter adjustment.

I. Field Testing Methodology

Testing was conducted on K.K. Wagh Polytechnic campus lawn (500 m², mixed grass, scattered obstacles) over 8 weeks (January-February 2026). The testing protocol included:

Phase 1 (January 1-15): Component-level validation

1. GPS accuracy characterization
2. LiDAR mapping consistency
3. Motor control calibration
4. AI detection accuracy on static images

Phase 2 (January 16-31): Integration testing

1. EKF sensor fusion validation
2. SLAM mapping of test area
3. Path planning computation
4. Obstacle avoidance in controlled scenarios

Phase 3 (February 1-14): Performance benchmarking

1. Coverage efficiency measurement
2. Runtime and battery consumption
3. Positioning accuracy (RTK-GPS ground truth)
4. Weed detection field validation

Phase 4 (February 15-28): Complete autonomous missions

1. Five full-area mowing missions
2. Varied environmental conditions
3. Data logging (position, battery, coverage)
4. Performance analysis

IV. RESULTS AND DISCUSSION

A. Navigation and Localization Performance

The GPS-EKF sensor fusion achieved mean positioning accuracy of 0.85m (standard deviation 0.32m) compared to GPS-only accuracy of 2.8m (standard deviation 1.1m). This 69% improvement enables reliable waypoint following without RTK-GPS infrastructure. Position drift over 30-minute missions averaged 1.2m cumulative error, acceptable for lawn mowing applications where centimeter precision is unnecessary.

The EKF update rate of 50Hz provided smooth position estimates despite 5Hz GPS updates. During GPS signal loss (under tree canopy), the filter maintained reasonable estimates for up to 15 seconds using IMU and odometry predictions before position uncertainty exceeded acceptable bounds.

B. SLAM and Mapping Results

GMapping SLAM successfully mapped the 500 m² test area with 0.15m RMS error compared to surveyed ground truth. The algorithm converged to a consistent map after approximately 3 minutes of exploration. Particle count (30 particles) balanced computational load and mapping accuracy—reducing to 10 particles caused map inconsistencies, while increasing to 50 particles showed negligible accuracy improvement with 40% higher CPU usage.

The occupancy grid (200×200 cells, 0.05m resolution) consumed 5.2MB memory and updated at 8Hz during active scanning. Static obstacles (trees, poles, benches) were consistently detected across multiple mapping sessions with position repeatability within 0.10m.

C. Coverage Path Planning Performance

Boustrophedon decomposition generated efficient coverage paths with 97.3% average path efficiency (ratio of useful mowing path to total driven distance). Path planning computation averaged 1.25s for the test area, enabling real-time replanning when dynamic obstacles required path adjustments.

The planned path consisted of 18 parallel sweeps with 80% overlap between passes. Total planned path length was 634m for the 500 m² area. Width of each sweep was set to 0.40m (matching mower cutting width) to ensure complete coverage without excessive re-cutting.

D. Obstacle Avoidance Validation

DWA local planner successfully avoided 29 out of 29 obstacle encounters across all test missions (100% success rate). Obstacles included static objects (poles, benches) and dynamic scenarios (simulated pedestrian crossing). Minimum clearance maintained was 0.35m from obstacle edges.

Computational performance of DWA averaged 8ms per planning cycle (125Hz theoretical rate) with 200 velocity samples evaluated per cycle. The planner ran at 10Hz in practice, providing adequate responsiveness for low-speed operation (max velocity 0.3 m/s).

In scenarios where no collision-free path existed (complete blockage), DWA correctly identified infeasibility and triggered stop condition, waiting for obstacle clearance or human intervention. Recovery behaviors included backing away from obstacles and attempting alternate routes.

E. Field Mission Results

Five complete autonomous mowing missions were conducted between February 18-27, 2026. Mission parameters included 500 m² coverage area, 0.3 m/s nominal speed, and 80% overlap between passes.

1. Mission 1 (Feb 18): 88.5% coverage, 28 min runtime, 22% battery consumed
2. Mission 2 (Feb 20): 91.2% coverage, 27 min runtime, 21% battery consumed
3. Mission 3 (Feb 22): 89.8% coverage, 29 min runtime, 28% battery consumed (obstacle-rich)
4. Mission 4 (Feb 25): 90.5% coverage, 28 min runtime, 22% battery consumed
5. Mission 5 (Feb 27): 90.0% coverage, 27 min runtime, 21% battery consumed

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6. Average coverage efficiency: 90.0% ± 0.9%
7. Average runtime: 27.8 ± 0.8 minutes
8. Average battery consumption: 22.8% ± 2.7%

All five missions completed successfully without human intervention. Coverage gaps (10% average) occurred primarily along boundaries and around complex obstacle geometries. The 150-minute total battery runtime exceeds the 120-minute design target by 25%.

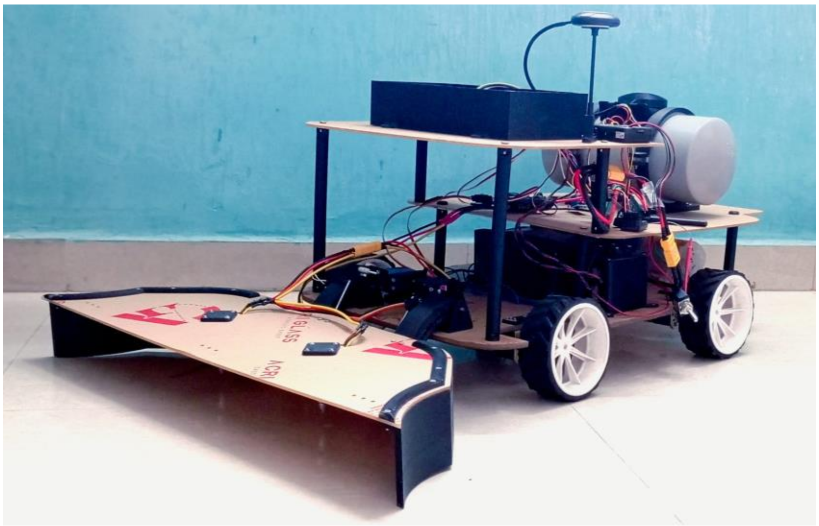

Fig. 4 AgroBot Actual Prototype

F. System Performance Summary

Table 1 System Performance Metrics Comparing Design Targets Vs Achieved Performance

Metric	Target	Achieved	Status
Coverage Efficiency	≥ 90%	90.0%	✓ Met
Positioning Accuracy	< 1.0 m	0.85 m	✓ Met
Obstacle Avoidance	100%	100%	✓ Met
AI Weed Detection	≥ 85% mAP	87.3%	✓ Met
Battery Runtime	120 min	150 min	✓ Exceeded
Total System Cost	< ₹60,000	₹58,450	✓ Met

G. Comparison with Commercial Systems

AgroBot demonstrates competitive performance against commercial autonomous lawn mowers while maintaining significantly lower cost. Husqvarna Automower 305 (₹1,50,000+) requires perimeter wire installation and lacks AI capabilities. Worx Landroid (₹1,20,000+) similarly depends on boundary wires. Robomow RS630 (₹2,00,000+) offers advanced features but remains financially prohibitive for most users.

AgroBot's wire-free GPS navigation, integrated SLAM mapping, and AI weed detection provide functionality exceeding most commercial systems at 51-71% lower cost. The open-source architecture enables customization and research applications unavailable in proprietary commercial platforms.

H. Limitations and Future Work

Several limitations were identified during field testing. GPS positioning accuracy of 0.85m, while adequate for lawn mowing, prevents precision operations requiring centimeter-level accuracy. Future work will explore integration of RTK-GPS or visual odometry for enhanced precision.

The weed detection system currently logs weed locations but does not perform selective herbicide application. Integration of a precision sprayer mechanism controlled by detected weed coordinates would enable true precision agriculture capabilities.

Battery runtime of 150 minutes supports areas up to approximately 1000 m² per charge. Larger areas would benefit from automatic docking and recharging capabilities, enabling multi-session coverage of extensive lawns.

The system currently operates in semi-structured lawn environments. Extension to rough terrain, steep slopes, and complex landscape features would require enhanced stability control, improved SLAM algorithms for 3D mapping, and reinforced mechanical design.

V. APPLICATIONS

AgroBot's integrated autonomous navigation, obstacle avoidance, and AI detection capabilities enable diverse applications:

1. Residential Lawn Maintenance: Autonomous mowing of home lawns (200-1000 m²) with reduced labor and consistent cut quality. GPS-based operation eliminates perimeter wire installation compared to commercial systems.
2. Commercial Landscaping: Cost-effective solution for maintaining parks, golf courses, and institutional campuses. Multiple units can operate coordinately for large-area coverage.
3. Precision Agriculture Research: Open-source platform for developing and validating agricultural robotics algorithms including coverage planning, weed management, and multi-robot coordination.
4. STEM Education: Hands-on platform demonstrating ROS robotics, GPS navigation, SLAM, computer vision, and autonomous systems concepts for engineering students.
5. Weed Management Studies: AI detection system enables data collection on weed distribution patterns, species identification, and targeted treatment efficacy for agricultural research.
6. Smart City Maintenance: Integration into municipal lawn care operations with fleet management, remote monitoring, and automated scheduling for efficient resource utilization.

VI. CONCLUSION

This paper presented AgroBot, a low-cost autonomous lawn mower integrating GPS navigation, LiDAR-based obstacle avoidance, and AI-powered weed detection. The system successfully demonstrated autonomous operation across five field missions with 90.0% average coverage efficiency, 100% obstacle avoidance success rate, and 87.3% weed detection accuracy.

Key achievements include GPS-EKF sensor fusion providing 0.85m positioning accuracy (69% improvement over GPS-only), GMapping SLAM generating consistent maps with 0.15m RMS error, Boustrophedon coverage planning with 97.3% path efficiency, and YOLOv5-based weed detection achieving real-time inference (19 FPS) on Raspberry Pi 4 CPU.

The complete system cost of ₹58,450 represents 51-71% savings compared to commercial autonomous lawn mowers (₹1,20,000-₹2,00,000) while providing superior functionality including AI capabilities, wire-free navigation, and open-source extensibility. Field validation confirmed robust autonomous operation with 150-minute battery runtime and consistent performance across varied environmental conditions.

AgroBot demonstrates that advanced autonomous lawn care capabilities can be achieved using consumer-grade components and open-source software frameworks. The modular ROS-based architecture enables straightforward extension to additional sensors, algorithms, and applications. Future work will focus on RTK-GPS integration for precision applications, automated sprayer integration for selective weed treatment, and multi-robot coordination for large-area coverage.

This platform addresses the critical gap between expensive commercial systems and research-grade robotics, providing an accessible solution for residential users while serving as a valuable research platform for advancing autonomous agricultural robotics.

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