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Intelligent Grass Cutting Robot with Computer Vision

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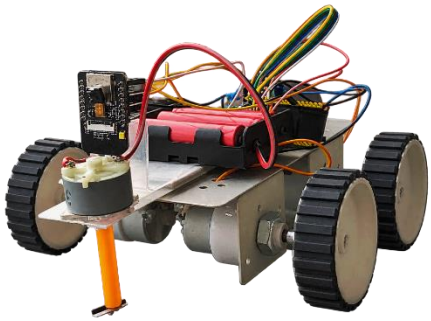
ABSTRACT :

Grass cutting is an essential maintenance task in gardens, parks, and lawns, but most existing grass-cutting machines operate continuously without distinguishing between grass and other green plants, which can lead to damage to flowers, shrubs, and ornamental vegetation. To overcome this limitation, this project proposes a Computer Vision-Based Autonomous Grass Cutting Robot that integrates computer vision with autonomous navigation to perform intelligent and selective grass cutting. The robot uses a camera to capture real-time images of its surroundings, and a trained deep learning model analyzes these images to identify grass while differentiating it from other green objects such as plants, flowers, shrubs, and obstacles. Based on the detection results, the system automatically activates the cutting blade only when grass is identified and keeps it turned off in all other situations, ensuring safe and precise operation. The robot is also capable of moving autonomously and avoiding obstacles, reducing the need for continuous human supervision. By combining artificial intelligence with an existing robotic platform, the proposed system aims to improve cutting accuracy, enhance safety, minimize damage to surrounding vegetation, and provide an efficient, eco-friendly, and intelligent solution for lawn maintenance in residential, commercial, and public green spaces.

Keywords: Autonomous grass cutter, Computer vision, Deep learning, Real-time object detection, Selective mowing, Autonomous navigation, Obstacle avoidance, Agricultural robotics.

Introduction :

Conventional robotic grass cutters operate indiscriminately without differentiating grass from desirable vegetation like flowers and shrubs, frequently causing unintended plant damage. To resolve this limitation, this project proposes an autonomous vision-guided grass-cutting robot integrating an ESP32-CAM module and a YOLOv11 deep learning model trained via Google Colab on a Roboflow dataset for real-time grass and vegetation classification. Equipped with ultrasonic sensors for collision avoidance, the system autonomously navigates the area and selectively actuates the cutting blade only when target grass is identified, keeping it deactivated around non-grass plants and obstacles. This integration of embedded vision, deep learning, and automated blade actuation delivers precise, selective cutting while safeguarding ornamental vegetation and minimizing the need for manual supervision.



Intelligent Grass Cutting Robot with Computer Vision

Literature Survey :

Autonomous Grass Cutting Rover

Built on a 3 mm plyboard chassis with rear geared DC motors and a front caster wheel, the mower uses an RS775 motor driving a 16 cm adjustable-height steel blade. Powered by a 12V lead-acid battery via MOSFET switching, the system navigates autonomously using a Raspberry Pi 4 and 5MP camera that process OpenCV vision routines for dynamic PWM steering and obstacle avoidance.

AI Based Grass Cutting Rover Using Image Processing to Move the Obstacle

The system utilizes a battery-operated four-wheel rover built on a mild steel chassis, driven by geared DC motors via an L298N H-bridge driver. A NodeMCU microcontroller coordinates obstacle avoidance using ultrasonic and infrared sensors, halting forward motion while actuating a front servo to clear small obstructions. A relay module switches a separate DC motor driving dual pulley-connected cutting blades, while wireless oversight and manual control are managed via Wi-Fi (Blynk) and an HC-05 Bluetooth module.

IOT Based Solar Grass Cutting Robot

The methodology centers on developing a solar-powered autonomous lawn mower constructed on a lightweight PVC pipe chassis, propelled by four 6-inch turbo wheels driven by 12V DC gear motors. Grass cutting is handled by a dedicated 12V DC motor rotating a stainless steel blade, powered by two 12V (1.3 Ah) batteries paired with an 18V, 27W monocrystalline solar panel for continuous recharging. Autonomous obstacle detection and navigation are executed by an Arduino microcontroller linked to a 40 cm range ultrasonic sensor, while an ESP-12E Wi-Fi module handles cloud telemetry and remote mobile application control.

Identification & Segmentation of Lawn Grass Based on Color & Visual Texture Classifiers

The methodology implements a vision-based freespace segmentation framework for real-time grass identification and obstacle avoidance without requiring LiDAR sensors. Digital images are partitioned into non-overlapping pixel neighborhoods (11×11 to 41×41 resolutions) evaluated through statistical HSI color analysis and Prewitt edge-filtered texture metrics. Texture is quantified using binary variance, edge area, and centroid image moments derived from the intensity plane, while color is validated against pre-trained grass hue thresholds. A normalized, weighted voting scheme across six classifiers subsequently fuses these descriptors to generate a binary probability map of drivable terrain to direct the robot's reactive navigation.

Design of General Kinematotropic Mechanisms

This 15-step kinematic framework uses displacement group theory to design kinematotropic mechanisms that bifurcate across operational modes without topological changes. By classifying joints into active and passive constraints across 18 basic serial chains, subchains are synthesized and verified at bifurcation singularities to ensure deterministic mode transitions.

Embedded Robust Visual Obstacle Detection on Autonomous Lawn Mowers

The methodology presents an embedded vision module retrofitted onto commercial lawn mowers to deliver non-contact obstacle avoidance across fluctuating outdoor lighting. Operating on an ARM-based phyFLEX-i.MX6 board interfaced via the mower’s CAN bus, the setup couples an automotive CMOS camera with closed-loop exposure/gain control and dual-frame HDR merging evaluated over real-time grass regions. Image processing employs an adaptive mean-shift tracking algorithm in HSV color space that continuously updates Gaussian hue and saturation distributions while filtering noise through connected components.

Vision-based Lawn Boundary Recognition for Mowing Robot

The methodology proposes a vision-based boundary detection pipeline that eliminates perimeter fence wires by classifying terrain textures under fluctuating illumination. Onboard grayscale images are partitioned into uniform grid patches, each processed through 18 multiscale Gabor filter configurations (6 orientations, 3 scales) to extract high-dimensional texture vectors. These features are compressed to 108 dimensions via Principal Component Analysis (PCA), normalized, and classified into grass or non-grass regions using an RBF-kernel Support Vector Machine (SVM) on an embedded Jetson TK1 board with row-consistency spatial filtering. By monitoring the segmented grass-to-frame area ratio, the robot executes proactive boundary maneuvers at 20% grass coverage and triggers an emergency stop or turning action if the area drops below 5%.

Image-Based Scene Recognition for Robot Navigation Considering Traversable Plants and Its Manual Annotation-Free Training

The methodology introduces an image-based perception and navigation framework built on an ESPNetv2 deep neural network backbone that operates without manual annotation. The architecture decouples scene understanding into two parallel branches: a Semantic Segmentation Module (SSM) for pixel-wise object categorization (plants, artificial objects, ground) trained via unsupervised domain adaptation with multi-source pseudo-labels, and a Traversability Estimation Module (TEM) that predicts pixel-wise traversability probabilities using intermediate features from the SSM. To overcome the scarcity of fine-grained plant labels, the TEM is trained using a Positive and Unlabeled (PU) learning formulation supervised by sparse "traversability masks" automatically generated from projected 3D paths traversed during preliminary mapping. During real-time navigation, pixel predictions are registered with RGB-D depth data, projected into a 3D semantic voxel grid, and temporally integrated using Bayesian updates; voxels identified as plants exhibiting traversability above a 0.75 threshold are classified as free space, enabling a mobile platform (Revast Mercury equipped with Kinect v2 and LRF) to plan paths through flexible vegetation using ROS move_base.

An Improved YOLOv8 to Detect Moving Objects

The methodology enhances the YOLOv8 single-stage object detection framework to specialize in detecting and localizing moving objects across dynamic video streams. The workflow executes across three stages: video preprocessing, deep architecture feature extraction, and post-processing. Preprocessing prepares video inputs by decoding frames, resizing them to standard dimensions, normalizing color values, and isolating dynamic elements via background modeling, frame differencing, binary thresholding, and morphological filtering. To handle motion artifacts like blur, occlusion, and scale variance, training incorporates advanced data augmentations (geometric transformations, random cropping, color jittering, MixUp, CutMix, and synthetic motion blur). The network architecture integrates Ghostblock units to lighten computational load, deeper residual convolutional blocks (leveraging ResNet structures), attention mechanisms, and a Bi-PAN-FPN feature fusion scheme for detecting small moving targets, optimized end-to-end using the Wise-IoU bounding box regression loss to balance scale and aspect ratio errors. Detections are refined through Soft-NMS to preserve overlapping objects in dense dynamic environments without premature suppression, coupled with motion-aware tracking across successive frames.

Object detection in real-time video surveillance using attention based transformer-YOLOv8 model

The methodology introduces a hybrid deep learning architecture that integrates a YOLOv8 backbone network with multi-head self-attention and a Transformer-based detection head to enhance real-time surveillance detection under occlusion and varying lighting conditions. Input video streams are preprocessed by extracting individual frames, resizing them to standard YOLO dimensions (416×416 or 608×608 pixels), and standardizing pixel intensities via z-score normalization. Spatial features extracted by the YOLOv8 CSPDarknet backbone and PANet neck are augmented with sinusoidal positional encodings and fed into a Transformer encoder-decoder network; this module leverages cross-attention and depth-wise separable convolutions to capture long-range dependencies, model global contextual relationships, and refine multi-scale feature representations while replacing traditional global reasoning for faster convergence. The fused feature maps are then routed through a Transformer-based detection head and a final output layer utilizing softmax classification and bounding box regression to generate precise bounding coordinates and class predictions at an inference speed of 5.2 ms per frame.

Methodology:

The fabrication process was carried out in systematic stages. Initially, the compact base frame and chassis were constructed to support mechanical loads and payload electronics. Next, the geared wheel motors and wheels were installed to establish mobility. The high-speed cutting blade mechanism and its protective safety bracket were mounted beneath the chassis. Following mechanical assembly, the electronic control hardware—including the main microcontroller, dual motor drivers, switching circuits, and ultrasonic sensor—was integrated and wired. The ESP32-CAM module was mounted at the front of the chassis to provide an unobstructed view of the cutting corridor ahead. Finally, the 3.7V-based Li-ion rechargeable battery pack and DC–DC buck voltage regulation circuits were integrated to provide a stable, self-contained, lightweight power source without reliance on external solar panels or support frames. After completing the full physical and electronic integration, the robot was tested to evaluate its drive maneuvering, real-time visual grass classification, obstacle detection response, and automated blade cut-off performance.

After installing all mechanical and electronic components, the complete robotic grass cutter with computer vision was assembled and tested. The robot was powered on to verify the operation of motors, sensors, and the cutting mechanism. Several tests were conducted to evaluate the movement of the robot, obstacle detection capability, and grass cutting efficiency. The robot successfully demonstrated its ability to move across the lawn while cutting grass and avoiding obstacles. The hybrid energy system ensured continuous operation using both solar and battery power. The successful fabrication and testing of the robotic system confirm that the proposed design is effective for lawn maintenance applications.

To enable autonomous visual navigation and real-time grass detection, the custom object detection framework was implemented using the state-of-the-art YOLOv11 architecture. The model was trained using Google Colab's GPU environment on a labeled dataset comprising two primary classes: "grass" and "no grass". This chapter presents the experimental dataset characteristics, training configuration, loss progression, and comprehensive validation performance.

PARAMETER	**VALUE**
Robot Weight	3 kg
Number of Wheels	4
Wheel Diameter	65 mm
Wheel Radius (R)	0.0325 m
Desired Speed	0.3 m/s
Grass Surface Friction Coefficient (M)	0.3
Gravity (G)	9.81 m/s²

PARAMETER	VALUE
Blade Radius	0.12 m
Cutting Rpm	4000 rpm

Specifications of the Components

Results & Discussion

The movement of the robotic grass cutter was tested on a grassy surface to verify the performance of the drive motors and wheel mechanism. The robot successfully moved forward, backward, and changed direction as controlled by the microcontroller. The DC geared motors provided sufficient torque to move the robot smoothly across the grass surface. The selected wheel size and motor speed ensured stable movement without slipping. The robot maintained proper balance due to the appropriate distribution of weight across the chassis. The movement test confirmed that the robot could travel effectively across the lawn while carrying all the mechanical and electronic components. The performance of the cutting mechanism was tested by operating the blade motor while the robot moved across grass surfaces. The high-speed rotating blade effectively cut the grass at the desired height. The cutting blade demonstrated smooth operation without excessive vibration. The blade motor provided sufficient power to cut both soft and moderately thick grass. The blade tip velocity calculated during the design stage was adequate to achieve efficient grass trimming. The grass cutting test confirmed that the developed system can perform lawn trimming effectively while maintaining consistent cutting performance. The overall stability of the grass cutter was evaluated during testing. The chassis structure remained stable while the robot moved across the grass surface. All mechanical and electronic components functioned properly during the testing phase. The integration of the control system, sensors, and mechanical components ensured reliable operation of the robot. The system demonstrated consistent performance during repeated trials without major operational issues. The experimental results confirm that the developed Intelligent grass cutting robot with computer vision performs according to the design objectives. The mechanical design calculations for motor torque, wheel speed, blade power, and battery capacity proved to be appropriate for the system requirements. The ultrasonic sensor enhanced the safety of the robot by enabling obstacle detection and avoidance. Although the prototype successfully demonstrated autonomous grass cutting, some improvements can further enhance system performance. These improvements may include advanced navigation algorithms, improved battery capacity, and additional sensors for better environment awareness. Overall, the proposed robotic grass cutting system provides an effective and environmentally friendly solution for automated lawn maintenance.

Conclusion :

The developed intelligent grass-cutting robot successfully demonstrates an efficient, eco-friendly solution for lawn maintenance by reducing human effort through autonomous navigation and computer vision. Ultrasonic sensors improve obstacle detection and avoidance, ensuring safer operation with minimal human intervention. Its cost-effective and energy-efficient design makes it suitable for small lawns, gardens, parks, and residential applications.

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