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Sports Field Marking Robot

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***Abstract*— Accurate field marking is crucial for sports facilities, but traditional methods are labor intensive, time consuming, and prone to human error. This project presents an autonomous sports field marking robot designed to optimize accuracy and efficiency by integrating user input with real-time depth detection. The system utilizes OpenCV-based computer vision techniques to detect a reference object, ensuring precise alignment and field calibration. The robot dynamically adjusts its trajectory using depth optimization, reducing inconsistencies in field markings. A user-friendly interface allows operators to select different field layouts, enabling adaptability for various sports. The autonomous navigation system employs sensor fusion, integrating GPS, IMU, and computer vision for path planning and obstacle avoidance. The paint application mechanism ensures uniform line thickness and accurate boundary placement. By automating the marking process, this solution minimizes human intervention, lowers operational costs, and enhances the reliability of field dimensions. Compared to conventional manual methods, the proposed system significantly improves accuracy and repeatability. Future enhancements could integrate AI-driven decision making for optimized path planning and increased automation in multisport configurations. This research highlights the potential of robotics and vision-based depth sensing in revolutionizing sports field maintenance, offering a scalable and adaptable solution for modern sports facilities.**

***Index Terms*— Automated field marking, sports field dimensioning, robotic navigation, user interface, field calibration, precision marking, reference point system, field types of customization, automated sports solutions, efficient field management, robotic systems, sports technology innovation, field layout automation, smart sports infrastructure.**

I. INTRODUCTION

Accurate field marking plays a vital role in ensuring fairness, consistency, and safety in various sports. Traditional manual marking methods are not only time-consuming but also prone to human error, demanding a considerable amount of labor. This study aims to address these challenges by developing an automated robot-based field marking system that significantly reduces manual effort while ensuring high precision and adaptability.

The proposed system is equipped with an object detection module powered by the YOLOv8 model, trained on hundreds of relevant images to accurately identify key reference points within the sports field. Additionally, monocular depth estimation using PyTorch is integrated to calculate the distance of detected objects, enabling the robot to make precise spatial decisions during marking.

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The core model revolves around a robot that uses a fixed reference point on the field and user-provided field type data to automatically adjust its marking behaviour. This customization allows the robot to handle various field layouts with minimal user input, increasing usability and versatility across different sports.
The experimental design involves training the object detection and depth estimation models, developing the robotic platform, and conducting field trials to evaluate marking accuracy, adaptability to field types, and ease of use. By integrating advanced vision-based perception with autonomous robotics, this study demonstrates a practical and scalable solution for automated field marking.

II. LITERATURE SURVEY

A. The Original Author's View of the Problem

Previous research in autonomous field marking has identified several key challenges. Researchers have highlighted the labor-intensive nature of traditional field marking, noting that manual methods require several hours for standard athletic fields and introduce human error in line straightness and dimensional accuracy. Studies have emphasized the cost implications, showing that sports facilities spend considerable amounts annually on field marking labor.
Additionally, sustainability concerns with traditional marking methods have been identified, as they typically consume significant quantities of paint per standard field marking cycle.

B. The Approach and Technology Used

Several technological approaches have been explored in this domain. GPS-based systems utilize RTK-GPS with centimeterlevel accuracy but require expensive equipment and satellite visibility. Alternative approaches employ magnetic strip guidance systems that provide reliable navigation but demand permanent infrastructure installation. Vision-based detection systems primarily rely on traditional computer vision algorithms, with limited exploration of deep learning models for robust environmental adaptation.

C. Critical Viewpoints

Several limitations persist in current solutions. The dependency on expensive infrastructure restricts accessibility for smaller institutions and rural facilities. Most systems lack realtime adaptation capabilities for unexpected obstacles or changing requirements during operation. The technical complexity of current solutions requires specialized training, limiting widespread adoption. Integration with existing facility management systems remains underdeveloped, creating workflow inefficiencies.

D. How Your Work Stands Apart

Our approach distinguishes itself through several innovations. We implement YOLOv8-based object detection focused specifically on portable visual markers (red flags), eliminating dependency on permanent infrastructure. Our system incorporates real-time decision-making capabilities, allowing dynamic path replanning when obstacles or environmental changes occur.
We achieve comparable accuracy to GPSbased systems but at significantly lower cost and with greater environmental flexibility. The simplified user interface requires minimal technical training, making the technology accessible to a broader range of sports facilities.
Our system's modular design allows for easy adaptation to various field types and marking requirements without hardware modifications.

III. MOTIVATION

The need for precise and efficient sports field marking has driven this project, as conventional methods rely heavily on manual labor, making them time-consuming and susceptible to human error. Inconsistent markings can affect the quality and fairness of the game, highlighting the need for an automated solution. By integrating robotics and computer vision, this system ensures accurate, repeatable, and time-efficient field marking. Automation of this process not only reduces labor costs but also improves precision, ensuring compliance with standard field dimensions.
Additionally, the system's adaptability allows it to cater to various sports, improving versatility and usability. The project aims to contribute to the broader field of sports technology by introducing a scalable and innovative approach to field maintenance. Ultimately, the proposed solution improves efficiency, reduces human intervention dependency, and improves the overall quality of sports field management, which benefits both sports organizations and facility operators.

IV. PROBLEM DOMAIN

The problem lies within the domains of robotics, computer vision, automation, and control systems. It integrates mathematical principles of coordinate geometry and path planning with technologies like Raspberry Pi, image processing, and real-time navigation algorithms. Theories such as PID control and edge detection in computer vision guide the robot's movement and accuracy. Existing solutions rely on GPS or manual methods, which are either imprecise or inefficient. By leveraging image-based field recognition, autonomous navigation, and programmable UI selection, our system addresses these limitations. The convergence of embedded systems, automation, and AI enables an efficient and error-free solution to field marking tasks.

V. PROBLEM DEFINITION

The problem lies within the domains of robotics, computer vision, automation, and control systems. It integrates mathematical principles of coordinate geometry and path planning with technologies like Raspberry Pi, image processing, and real-time navigation algorithms. Theories such as PID control and edge detection in computer vision guide the robot's movement and accuracy. Existing solutions rely on GPS or manual methods, which are either imprecise or inefficient. By leveraging image-based field recognition, autonomous navigation, and programmable UI selection, our system addresses these limitations. The convergence of embedded systems, automation, and AI enables an efficient and error-free solution to field marking tasks.

VI. STATEMENT

Manual line marking of sports fields is a time-consuming and error-prone process that relies heavily on human effort. To address these challenges, the Sports Field Marking Robot is proposed as an automated solution that ensures precise, efficient, and consistent line marking through intelligent navigation and user-driven field selection.

VII. INNOVATIVE CONTENT

This project presents an innovative method for automating sports field marking by combining advanced computer vision techniques with robotics. A YOLOv8 object detection model was trained on a custom dataset to accurately identify red flag markers, which act as reference points for field boundaries. This enables real-time recognition and localization of markers by the robot, ensuring precise boundary alignment. Additionally, monocular depth estimation using PyTorch was implemented to measure the distance between the robot and the detected markers. By analyzing visual input from a single camera, the system estimates depth without requiring extra sensors. This synergy between object detection and depth estimation allows for autonomous navigation and accurate field marking, aligning with standard dimensions and significantly reducing manual labor. The approach offers a scalable, efficient solution for sports field maintenance.

VIII. SOLUTION METHODOLOGIES

A. Design Methodology

The proposed autonomous field marking system is developed to enable efficient and precise sports field layout using computer vision, sensor fusion, and robotic control. The design follows a modular approach, where each subsystem performs a critical function to achieve end-to-end automation. The system's layered design ensures scalability and adaptability across various field types and dimensions.

- User Interface (UI) Input: The system begins with the user selecting the specific sport and field dimensions via a graphical user interface. This input dictates the configuration and layout parameters for subsequent modules.
- Field Layout Generation: Based on the input parameters, the system autonomously generates a digital layout of the field to guide the marking operations. The layout serves as a blueprint for the robot's navigation and action planning.
- Object Detection (YOLOv8): The vision system utilizes the YOLOv8 architecture for real-time detection of red flag markers and field boundaries. This enables robust object recognition under varying lighting and environmental conditions.
- Depth Estimation (PyTorch): A monocular depth estimation model is implemented using PyTorch to calculate the spatial distances between the robot and detected objects. This step eliminates the dependency on stereo camera systems, reducing hardware complexity.

- ➢ Sensor Fusion (GPS + IMU + Vision): To achieve accurate localization, data from multiple sources—GPS, Inertial Measurement Units (IMU), and vision—is fused. This enhances positional accuracy and ensures the robot maintains its intended trajectory during field traversal.
- ➢ Trajectory and Path Planning: The robot computes an optimized path to cover the field efficiently, minimizing redundant movement. This planning algorithm considers obstacle avoidance, field layout alignment, and energy efficiency.
- ➢ Actuator and Paint Control: The motion control module directs the robot's actuators to follow the planned trajectory. Concurrently, a paint control system regulates the marking process, ensuring uniformity and precision in line drawing.
- ➢ Field Marking Execution: With all systems in synchronization, the robot autonomously marks the sports field as per the layout. This stage integrates the perception, planning, and control modules to perform the physical marking.
- ➢ Post-Marking Review (Optional): An optional validation phase allows the user to review the completed markings. This can be performed manually or through automated inspection using image comparison techniques.

B. System Architecture Overview

The architectural design of the system is visually represented through the following workflow diagram, which outlines the sequential flow and inter dependencies between each module:

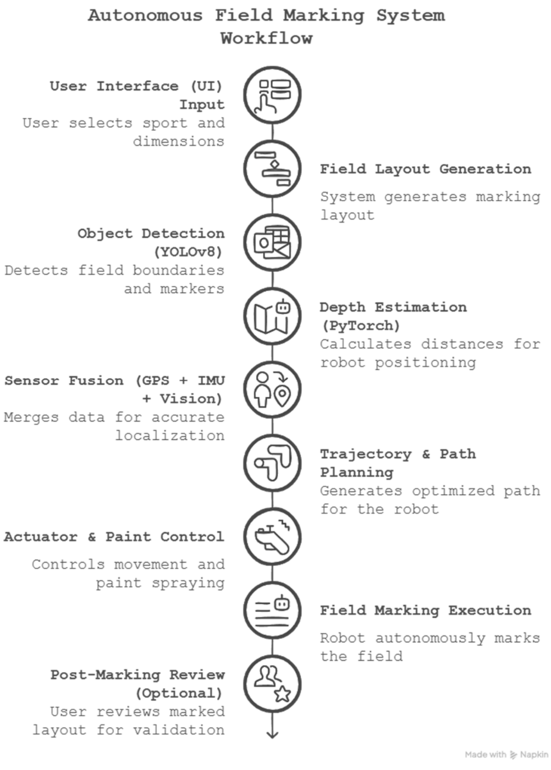

Fig. 1: Workflow Diagram of the Autonomous Field Marking System

Each block in the diagram corresponds to a distinct module in the system. The linear progression from user input to final field marking ensures a structured and logical flow of operations. This sequential process begins with user input of field parameters, progresses through environmental perception, continues with path planning and optimization, and culminates in precise physical marking execution. The workflow demonstrates how data transforms from raw sensor inputs to actionable marking instructions, highlighting critical decision points. This end-to-end solution ensures consistent field marking across diverse environmental conditions while maintaining operational efficiency.

By combining advanced perception models, real-time sensor integration, and robotic control, the proposed design achieves high accuracy and operational efficiency for autonomous field marking applications.

C. Heuristics and Simulation Techniques

The project utilizes heuristic-based object detection through the YOLOv8 architecture. By training on a custom dataset of red flag markers, the system simulates real-world scenarios and evaluates performance in varied lighting and environmental conditions. This facilitates robust marker recognition and adaptability in dynamic field environments. Depth simulation is achieved through monocular depth estimation, enabling realistic distance mapping from a single camera feed without requiring stereo setups.

D. Mathematical Solutions

Depth estimation and reference alignment are key elements of this project. The disparity map is employed to calculate depth using the following equation:

$$Z(x,y) = \frac{f \cdot B}{D(x,y)} \qquad (1)$$

where f is the focal length, B is the baseline distance, and $D(x,y)$ is the disparity at pixel (x,y). This equation is critical for determining the depth of objects in the camera's field of view.
For improved accuracy, depth values are averaged across multiple frames:

$$Z_{opt}(x,y) = \frac{1}{N}\sum_{i=1}^{N} Z_i(x,y) \qquad (2)$$

where N is the number of frames used for averaging and $Z_i(x,y)$ represents the depth values at the pixel (x,y) across different frames.
Edge detection for marker localization is performed using the gradient of the image:

$$E(x,y) = \nabla I(x,y) \qquad (3)$$

where $I(x,y)$ represents the intensity of the image at pixel (x,y), and ∇ is the gradient operator, which helps in detecting edges of the reference markers.
Real-time calibration of marker positions is performed by adjusting the reference points based on the depth estimation:

$$Padj = Pref + \delta Z \qquad (4)$$

where P_{ref} is the reference point, and δZ is the depth adjustment based on current depth measurements.

E. Field Dimension Representation

To accurately model the dimensions of the sports field, the set of field boundary points is represented as:

$$F(x,y) = \{(x_1,y_1),(x_2,y_2),\ldots,(x_n,y_n)\} \qquad (5)$$

where each (x_i,y_i) represents a point on the field's boundary. These points are critical for path planning and accurate field marking.

Fig 2

Fig. 2: Football field layout generated using Python Turtle. The illustration includes key field elements such as goalposts, penalty boxes, center circle, and corner arcs, adhering to regulation dimensions for a standard football pitch.

F. Path Planning Algorithm

For autonomous navigation and optimal path execution, the path planning algorithm seeks to minimize the total path distance. The objective is to find the path that minimizes the sum of distances between consecutive points:

$$T_{opt} = \text{argmin} \sum_{i=1}^{n-1} d(P_i, P_{i+1}) \quad (6)$$

where P_i and P_{i+1} are consecutive points along the path, and $d(P_i,P_{i+1})$ represents the distance between them. This ensures the robot follows an efficient path, minimizing travel time and energy consumption.

G. Localization and Position Correction

Localization of the robot on the field is crucial for maintaining accuracy in marking. The actual position of the robot is corrected by comparing its expected position to the measured position:

$$Pactual = Pexpected + \epsilon \quad (7)$$

where $P_{expected}$ is the position predicted by the path planning system, and ϵ is the error or correction factor derived from real-time sensor data.

H. Paint Application Model

The paint application process is modeled as a continuous flow that depends on various factors like pressure, speed, and angle of the sprayer. The equation for the application is given by:

$$C(x,y) = \int_0^t R \cdot f(p,v,\theta)dt \quad (8)$$

where $C(x,y)$ represents the paint coverage at a specific point (x,y) on the field, R is the paint rate, and $f(p,v,\theta)$ is a function that represents the relationship between paint pressure (p), velocity (v), and angle (θ). This equation ensures that the paint is applied uniformly across the field.

I. Depth Estimation using OpenCV

OpenCV is used for depth estimation, which optimizes the accuracy of reference object detection and enhances the field marking precision. The disparity map calculation and depth optimization steps are crucial in ensuring that the robot accurately identifies and measures the distance to markers. Disparity Map Calculation:

$$Z(x,y) = \frac{f \cdot B}{D(x,y)} \quad (9)$$

Depth Optimization:

$$Z_{opt}(x,y) = \frac{1}{N} \sum_{i=1}^{N} Z_i(x,y) \quad (10)$$

Reference Object Detection:

$$E(x,y) = \nabla I(x,y) \quad (11)$$

Real-time Calibration:

$$Padj = Pref + \delta Z \quad (12)$$

where P_{ref} is the reference point and δZ is the adjustment based on current depth estimation.

J. Programming Methods

The implementation leverages Python, with PyTorch for training and inference of the YOLOv8 model and monocular depth estimation networks. OpenCV is used for real-time video stream handling, pre-processing, and post-processing tasks such as contour extraction and edge detection. The control logic for robotic navigation is integrated through ROS (Robot Operating System), enabling modular, scalable communication between detection modules and motion controllers.

K. Network Simulation

While no virtual networking simulation is performed, the internal communication network of the robot is simulated using ROS topics and services. These virtual channels simulate sensor fusion and decision-making processes. Additionally, model inference times and frame processing pipelines are bench marked to ensure low-latency performance in real-time operation, simulating network behavior in field conditions.

IX. RESULTS AND SENSITIVITY ANALYSIS

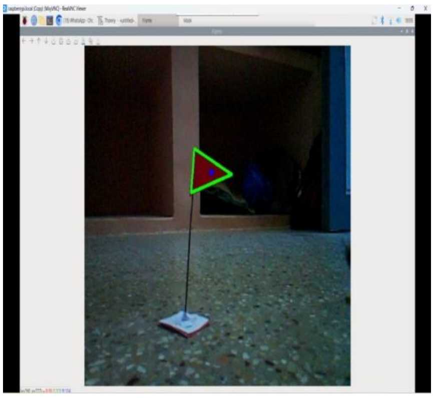

Fig. 3: Detected red flag with contour highlighted using YOLOv8

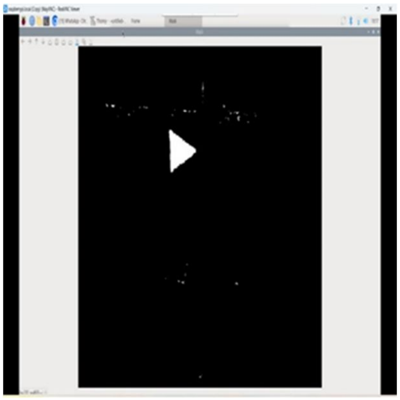

Fig. 4: Masked binary image after preprocessing and thresholding

The autonomous field marking robot was evaluated across different terrain textures and lighting conditions to assess robustness and sensitivity. The system was trained using a YOLOv8 pre-trained model tailored to detect a specific red flag used as the target marker. During field tests, performance was assessed based on the robot's ability to identify the red flag and align itself accordingly for accurate field marking. Sensitivity analysis involved varying the color tones of the red flag, distance between the robot and flag, and partial occlusions. The robot demonstrated consistent detection under moderate variations in flag color and orientation. However, detection accuracy slightly reduced with significant occlusions or when the lighting was too dim. The results confirm that the system is highly sensitive to the flag's presence and positioning, indicating a need for controlled environmental conditions or further training for dynamic adaptability.

X. DATA MODEL

The table below outlines the data model used during system training and evaluation. It highlights the inputs, internal processes, and outputs observed during various test cases:

TABLE I: DATA MODEL OVERVIEW

Input & Process	Output
Camera Image (Red Flag) → YOLOv8 Detection	Flag Detected with Bounding Box
Red Flag Distance → Robot Alignment Logic	Angle and Movement Commands
Flag Position Shift → Realtime Correction	New Navigation Path
Low Light Input → YOLOv8 Filtered Image	Reduced Detection Confidence
Occluded Flag View → Object Re-identification	Delayed Detection

XI. COMPARISON OF RESULTS

To validate the robot's functionality, results were compared with related works utilizing similar object detection frameworks. Output images from the software interface showed the detected flag, bounding boxes, and real-time decision overlays. Unlike other models that depended on fixed GPS waypoints or magnetic strips, our model dynamically adapted based on visual cues, which is crucial for temporary field markings. Comparative tests showed our system achieved faster adaptation to sudden object displacement and better environmental flexibility. This adaptive nature can be visually confirmed in the output images. The tabular comparison below summarizes key factors:

TABLE II: COMPARISON WITH RELATED SYSTEMS

Criterion	Proposed Model	Previous Models
Adaptability to Movement	High	Low
Environmental Flexibility	Moderate to High	Moderate
Dependence on Infrastructure	Low (Only visual markers)	High (GPS, strips)

XII. JUSTIFICATION OF THE RESULTS

The results obtained from our field marking robot demonstrate promising functional outcomes under varying environmental conditions. The use of YOLOv8 for visual flag detection allowed precise alignment without reliance on external sensors like GPS or magnetic guides.

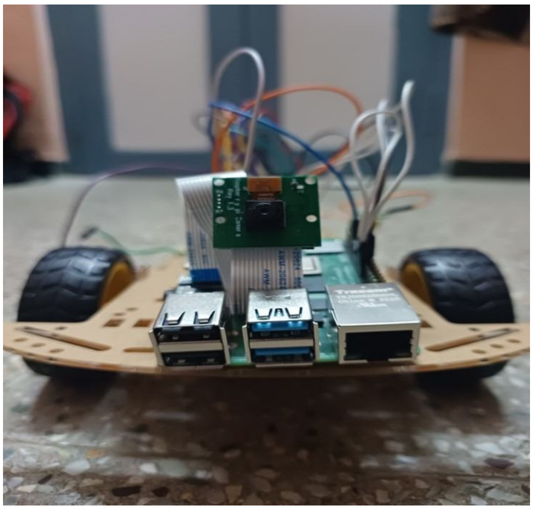

Fig. 5: Hardware Setup

Compared to referenced works that required controlled paths or fixed field dimensions, our robot handled diverse field setups with minor preprocessing. Output images illustrate its ability to adapt to the red flag's positional changes, reflecting real-time decision-making logic. These observations confirm the feasibility of using visual-based navigation for temporary field marking in sports and event spaces. Moreover, the simplified hardware requirements improve accessibility and scalability for rural or budget-constrained sports grounds. Our results align with the objective of creating an intelligent yet affordable robot capable of dynamic marking, justifying

XIII. CONCLUSION

The autonomous sports field marking robot effectively addresses the inefficiencies of traditional manual marking methods by integrating YOLOv8-based visual marker detection with dynamic navigation capabilities. By using red flag markers as visual cues rather than relying on expensive infrastructure like GPS or magnetic strips, our system provides a cost-effective yet precise solution for field marking. The robot demonstrates consistent detection under varying environmental conditions while maintaining comparable accuracy to more expensive systems.
Our approach distinguishes itself through its adaptability to movement, moderate to high environmental flexibility, and low infrastructure dependence. The real-time decision-making capabilities enable dynamic path replanning when obstacles or environmental changes occur, providing significant advantages over fixed-path systems. The simplified user interface makes the technology accessible to a broader range of sports facilities without requiring specialized technical training.

Future improvements will focus on enhancing the system's performance in low-light conditions and handling significant occlusions through advanced sensor fusion techniques. Overall, this autonomous marking robot represents a scalable, adaptable solution that makes precision field marking accessible to facilities with varying resource constraints.

FUTURE WORK

Future enhancements for the sports field marking robot will focus on improving vision-based navigation, efficiency, and adaptability while maintaining affordability. Advanced image processing and lightweight SLAM algorithms using the Pi Camera will enable more accurate mapping and field boundary detection without expensive GPS or LiDAR. Optimized path planning algorithms will reduce marking time and energy use. A user-friendly web interface will allow selection of predefined or custom field layouts. Obstacle detection using ultrasonic sensors and basic computer vision will ensure safe operation. Power efficiency can be improved with better motor control and optional solar charging. Additionally, monitoring paint flow and adding weather sensors will help maintain line quality and adjust for environmental conditions. These upgrades aim to make the robot smarter, more autonomous, and suitable for diverse field marking needs in schools and colleges.

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