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Article

Analysis of Football Pitch Performances Based on Different Cutting Systems: From Visual Evaluation to YOLOv8

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Abstract: The quality of sports facilities, especially football pitches, has gained significant attention due to the growing importance of sports globally. This study examines the effect of two different cutting systems, a traditional ride-on mower and an autonomous mower, on the quality and functional parameters of a municipal football field. The analysis includes visual assessments, measurements of grass height, and evaluations of surface hardness, comparing the performance of the two cutting systems. Additionally, studies of turfgrass composition and machine learning techniques, particularly with YOLOv8s and YOLOv8n, are conducted to test the capability of assessing weed and turfgrass species distribution. The results indicate significant differences in grass color based on the position (5.36 in the corners and 3.69 in the central area) and surface hardness between areas managed with a traditional ride-on mower (15.25 Gmax) and an autonomous mower (10.15 Gmax) in the central region. Higher height values are recorded in the area managed with the ride-on mower (2.94 cm) than with the autonomous mower (2.61 cm). Weed presence varies significantly between the two cutting systems, with the autonomous mower demonstrating higher weed coverage in the corners (17.5%). Higher overall performance metrics were obtained through YOLOv8s. This study underscores the importance of innovative management practices and monitoring techniques in optimizing the quality and playability of a football field while minimizing environmental impact and management efforts.

Keywords: autonomous mower; visual quality; cutting performances; machine learning; weed

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1. Introduction

In recent years, the importance of sport, such as football, has become very evident due to the increasing number of sports facilities [1]. Football is one of the most popular sports in the world, and football-related business plays a key role in international business trade and the economy [2]. To respond to players, fans, and shareholders, soccer pitch quality has to be maintained at a suitable level both for the aesthetic side and playability [1]. According to Grossi et al. [3], rapid runs and effective ball control are assured by a high-quality and homogeneous turfgrass. In this regard, a soccer pitch should consist of a turfgrass able to adapt to the environment and able to create good coverage on the entire interested area. Turfgrass areas benefit greatly from strong, dense cover because it keeps the lower layer of soil loose and prevents compaction [4]. In addition, according to Russo et al. [5], besides the aesthetic visual quality, turfgrass can create safer conditions for players by, for example, absorbing sun rays and reducing their effects on the eyes and by creating a soft ground to reduce the injury effect on players' bodies. Miller et al. [6] identify three main characteristics of a soccer pitch surface that play a main role in player safety and performance and ball response: hardness, evenness, and homogeneity. A bumpy and bare surface can cause uneven and unpredictable ball rebounding and rolling, and it can negatively affect the game [7]. In this regard, according to Puhalla et al. [8], smooth, consistent turf is necessary for players to pass and shoot with perfect accuracy because it allows the ball to roll straight and decisively. The field coverage with turfgrass, together with correct irrigation and water drainage, affects playability and safety: the risk of injuries from the ground is increased when players are forced to deal with mud on a field with lacking turfgrass and exposed dirt, particularly on wet days [9]. Turf height affects turf quality and soccer-playing characteristics [10]. According to Özkan et al. [9], the mowing height is strictly related to the ball response, and the football pitch needs short and proper mowing activity; in fact, when a ball rolls across a short-cut turf surface, it encounters less resistance and can go in the intended direction without bouncing. In addition, mowing, as the cutting or leveling activity at a certain height at certain intervals according to the cutting machine employed, helps to keep the turfgrass healthy and also eliminates some pests [11]. According to Staněk et al. [12], biomass removal which occurs during mowing is a crucial part of considering having high-quality turfgrass. However, adequate turfgrass quality depends on the context, where turf species, cultivars, and mowing activity can be very different [13]. Recently, the demand for sports surfaces has been oriented based on criteria of constant and standardized quality, resistance to very high volumes of play, and the absence of almost total susceptibility to environmental conditions [14].

All the necessary management to fulfill the quality and playability standard involves operating costs and annual maintenance requirements [5]. The LCA analysis conducted by Russo et al. [5] on natural and artificial turfgrass recognizes weeding and cutting as periodic and main operations in a natural soccer pitch. Regarding mowing height, the FIFA standard establishes a standard height of around 25–30 mm, which can be obtained through different types of machines. Through the traditional one, the cutting activity is conducted two or three times a week following the "1/3 rule. Instead, through innovative technologies such as robot mowers, mowing activity is usually conducted every day, and only a small amount of leaf tissue is cut at a time. In this way, together with grasscycling, a high degree of photosynthesis and carbohydrate generation for new tissue growth and higher quality is ensured [13,15]. Innovative technologies such as advanced path planning algorithms for different mobile robots, including autonomous mowers, could optimize mowing trajectories to enhance the efficiency and accuracy of path planning [16]. Trajectory optimization could also avoid unnecessary repeated passes on the turf, which may affect turf quality in terms of density and resilience [17].

In sport green areas, as in recreational green areas, turfgrass is preferable because it has homogenous coverage with a very low presence or complete absence of weeds. The product application could be conducted to stop the proliferation of weeds, but according to global efforts to minimize chemical input, agronomic techniques, frequent mowing activity, or innovative ways for early weed detection are preferred [18]. In this regard, it is also useful to highlight the European Union's directives, which consist of a strict synthetic herbicide ban due to exposure causing health and environmental risks. Among the innovative methods of weed management are image processing, machine learning, and computer vision techniques [19]. According to Wang et al. [20], the development of the abovementioned techniques, in particular the computer vision techniques and deep learning models, has allowed precise target detection and in this way has improved detection performance for implementation in agricultural production. These techniques are often focused on detection of the main crop, but many studies are emerging about weed classification. For example, deep learning algorithms for semantic segmentation assigning a label or a category to every pixel of an image can be a promising method [21].

Typically, weed detection relies on plant features such as morphology, leaf texture, and color [22,23]. It is easier to identify weeds in dormant turfgrass than in actively growing turfgrass. Moreover, detecting large-leaved weeds is easier than detecting small-leaved ones, and it is simpler to identify broadleaf weeds than grasses or grass-like weeds in turfgrass [24,25]. However, detecting and classifying weeds can be challenging due to their similar colors, morphologies, and textures compared to turfgrass [26]. Therefore, some problems occur in the detection of weeds, especially on highly similar backgrounds, but they can be solved thanks to the increasing capability of detection networks, such as YOLO (You Only Look Once). The recognition of weeds assured by these methods can be seen as the first step towards field mapping, which can guide the operators in site-specific weed management, deciding if the presence of weeds can compromise the quality or the performance (such as for a soccer pitch) of their green areas.

The widespread use of pesticides to control pest populations is one of the most common and effective practices to ensure high-quality playing surfaces. However, adopting alternative, pesticide-free methods—such as frequent mowing with autonomous mowers, precise floristic analysis of the turfgrass, and also the acceptance of turfgrass with diverse species—can make it more challenging to maintain an adequate playing surface [27]. Additionally, turfgrasses are often established with only one or a few cultivars, which in many cases creates suboptimal environments where even minor stress can make the turfgrass more susceptible to disease and pest attacks. For these reasons, the use of pesticides remains the accepted and necessary paradigm for chemical control; however, reducing the environmental risks associated with pesticide application is a key priority on the environmental protection agenda.

This study aims to analyze two different cutting activities (a robot mower with systematic trajectories vs. an endothermic ride-on mowing machine) that affect the quality and functional parameters of an amateur municipal football field. This soccer pitch was characterized by a non-homogenous floristic composition. In this regard, the analysis aims to verify the differences between a traditional and an automatic cutting system and to see the correlation of the different species distribution within the soccer pitch and their possible correlation with the playing surface quality.

In the future perspective of implementing autonomous mowers with real-time weed recognition capability, YOLOv8s and YOLOv8n have been tested. The purpose of this investigation was to evaluate the segmentation ability to precisely target and separate different weed species, possibly displacing the time-consuming field-scanning procedure that operators typically perform to monitor the spread of weeds. The choice to test the segmentation capabilities on a turfgrass rich in diverse species was motivated by the need to address the complexity of feature extraction. Indeed, according to Jin et al. [26], including a broad range of weed species and ecotypes in the training and testing datasets is essential to ensure accurate performance in turfgrass management scenarios; this species variety would help improve the performance of the weed detection system.

2. Materials and Methods

The trial was carried out at the municipal football pitch of Vecchiano-Nodica (Pisa, 43°47′03″ N 10°22′28″ E). The area consisted of a mature turfgrass stand of bermudagrass (*Cynodon* spp.) and clover (*Trifolium* spp.) severely infested by different species. The area's size of 5200 m^2 (104 m of length and 50 m of width) corresponds to the standard measures of a Junior football pitch according to McGeary [28]. The initial species coverage was visually assessed to be around 45% for bermudagrass, 35% for clover, and 20% for other weeds. Three soil samples (10 cm of soil) were collected randomly, and each soil sample consisted of 5 subsamples, which were mixed and collected separately. The samples were collected outside the playing area in an area not affected by cutting or trampling activity. Through analysis of these samples, it was established that the turfgrass was established on sandy loam soil characterized by the following physical–chemical properties: 76% sand, 14 silt, 10 clay, pH of 7.9, and 2.9% organic matter [29].

Before the beginning of the trial, the entire area was managed with an endothermic ride-on mowing machine with a mowing height of 2.7 cm two times a week. Irrigation was provided only to supplement rainfall and to avoid any potential turfgrass stress. No fertilization or weed control was conducted. Data regarding the average temperature and rainfall during the test period (from July 2023 to January 2024) are reported in Figure 1.

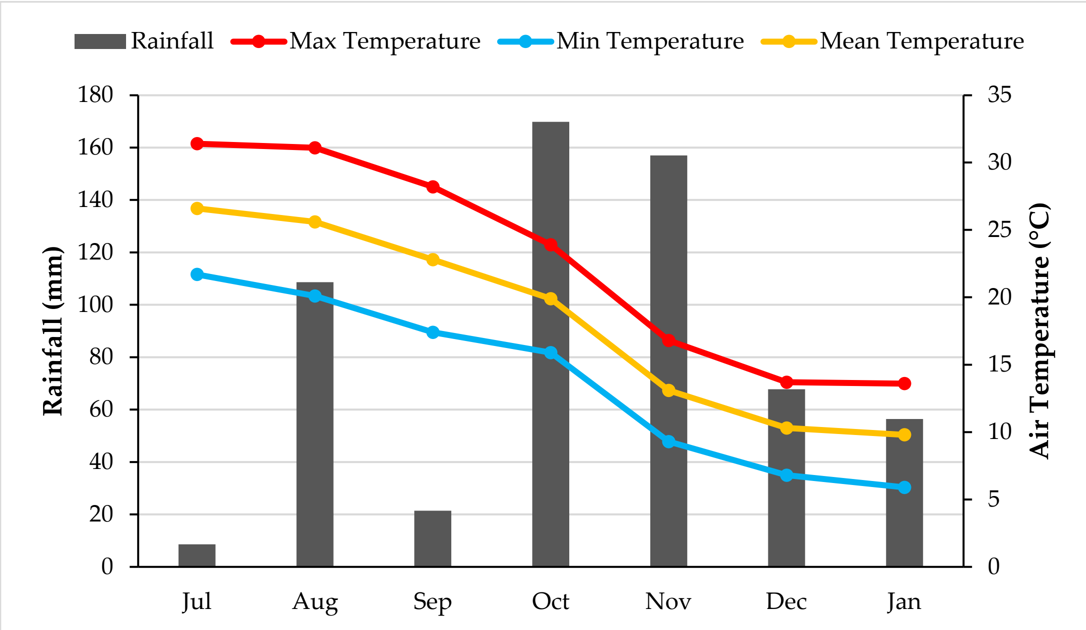


Figure 1. Weather conditions during the trial period.

2.1. Experimental Field Trials

From July 2023 to January 2024, two areas of 2600 m^2 corresponding to two halves of the same soccer pitch were identified. The experimental layout was a completely randomized block with three replications for two different machines. The main factors of the analysis were the management type and the position within the soccer pitch to assess the turfgrass height, quality, color, the surface hardness, and the turfgrass composition.

The cutting machines employed were a ride-on mower (RM) equipped with a 100 cm cutting deck characterized by an electric adjustment of cut height and an autonomous mower (AM); both machines operated with a systematic pattern (Figure 2).

(**a**) (**b**)

Figure 2. The two different cutting systems in the selected soccer pitch: (**a**) the autonomous mower with systematic trajectories and (**b**) the ride-on mower.

Main characteristics of the machines employed are shown in Table 1. The two machines were set to work for a different amount of time in each plot; the autonomous mower was set to work every day from 11:00 p.m. to 11:00 a.m., and the ride-on mower worked twice a week in the autumn period and three times a week in the summer one.

Table 1. Cutting systems' manufacturing features.

Parameter	Unit	Autonomous Mower	Ride-On Mower
Dimension (Lenght × Height × Width)	cm	72 × 32 × 56	104.3 × 30.5 × 107.4
Mass	kg	13.8	282 *
Cutting width	cm	24	100
Cutting height	cm	2.5	2.5

* 230 kg (machine) + 52 kg (cutting disk).

2.2. Assessments

The turf height was measured by a grass height meter once a week before and after the ride-on mower activity. The quality parameters of the turfgrass were calculated based on the quality and the color visual assessment, conducted by a skilled and trained turfgrass expert, and they were also correlated to its composition. Four sub-replications were conducted to assess the visual parameters of color and quality and the turfgrass composition before and after each mowing event. The color and quality values were assigned based on a 1–9 colorimetric and quality scale described by Luglio et al. [13].

A Clegg Impact Tester was employed to measure the surface hardness (G_{max}) differences between the areas mowed with the two cutting methods. The measurements were carried out in specific areas, the same areas of quality and color evaluation. The areas were chosen based on those that are usually most trampled during football matches according to Miller et al. [6]. Further analyses were conducted to assess the soil water content, the electrical conductivity, and the temperature with the time-domain reflectometry (TDR), and these data were collected to better detect any differences in the soccer pitch and to better understand the Clegg Impact Tester results.

To complete the data collection on the quality and performance parameters of the turf, a survey was set up and submitted to the maintenance workers and coaches of the football field. This survey was set to complete the data collection and understand if any differences were detected in the two areas cut with two different cutting systems. At the beginning of the questionnaire, three open questions were asked:

- Have you noticed a difference between the two halves of the field?
- Did the autonomous mower presence disturb matches and training sessions?
- Have you noticed any different mechanical abrasions?

In the second part of the survey, they were asked to give a judgment (high (9), medium (4,5), low (1)) regarding the qualitative parameters (color, density, uniformity), the athlete–surface interaction (traction, hardness, slipperiness), and ball–surface interaction (bounce, slide). Before submitting the survey, the meanings of all the parameters to be evaluated were explained in detail.

Data on percentage of area mowed and the distance travelled were collected through two Emlid Reach RTK (Emlid Tech Kft., Budapest, Hungary) devices to assess the total cutting coverage of robot mower. The two Emlid Reach RTK devices employed are described in detail by Luglio et al. [13]. Data on the actual cutting time were taken from the robot mower application, which gave us precise information about robot mower position and status in terms of cutting, parking, charging time, and the number of errors that occurred. Data regarding the ride-on mower were manually measured and consisted of the average speed, the time to complete an entire passage along the field, and the time to turn at the end of the field. All these data were used to assess the operative performances of the two cutting machines.

Values regarding primary energy consumption were calculated. The robot mower's primary energy consumption was calculated according to the weekly consumption of mowing half of the soccer pitch, the time was recorded by the abovementioned robot mower application, and the power energy consumption during the mowing activity was

0.035 kWh $\cdot$ h^{-1}. The ride-on mower's primary energy was calculated according to the hourly gasoline consumption (*Ch* = kg gasoline kWh^{-1}) using Equation (1):

$$Ch = W \times d \times h \quad (1)$$

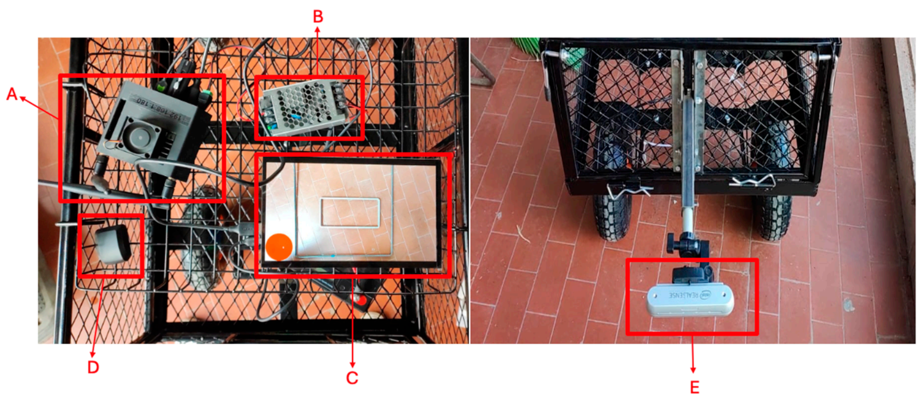
where the *W* is the power of the engine (11.82 kW), *d* is the effort percentage of the cutting machine (0.5), which was assigned depending on the amount of green biomass present, and *Cs* is the energetic efficiency of the ride-on mower engine (0.35 kg fuel kWh^{-1}). The primary energy consumption estimation also considered the gasoline heating value, which is 12.22 kWh kg^{-1}. The working schedule considered the working schedule of the football pitch manager, which was two times a week for 0.5 h.

2.3. Floristic and Species Distribution Analysis Within the Soccer Pitch

In order to analyze the weeds and turfgrass species present in the two halves managed by the two different cutting systems, an homogenous dataset was collected in specular zones of the soccer pitch. These photos were analyzed to recognize the different species located in the soccer pitch, and then, after the data collection described in Section 2.3.1, the images were annotated and converted into YOLOv8 version format though the Roboflow API "https://app.roboflow.com, (accessed on 12 March 2024)".

2.3.1. Dataset Creation

The dataset was created by taking photos using a preliminary image acquisition system, set up in collaboration with Aitronik team (Figure 3). The main object of this research activity is to acquire images from an RGBD camera (Realsense D435F, Intel, Santa Clara, California, USA), catalogue them based on GPS position (NMEA protocol), record the date and time of acquisition, and finally save them on a USB pen drive. For this purpose, a Jetson dwarf was chosen. The software used to interface with the various sensors is ROS 1, a system that allows the rapid and efficient exchange of data between sensors. The SW is initialized by opening the RGBD camera stream and periodically acquiring both an RGB image, a DEPTH, and finally an infrared one, and only the last available RGB image is displayed on the screen. There are 2 buttons on the screen, one to set a timer which can have the following values: 0 s (single photo), 1s, 2 s, 3 s, 4 s, 5 s. At each cycle of the timer, the 3 images are essentially saved inside the USB pen drive, and finally they are renamed based on the position given by the GPS at that moment and the current date and time. If the GPS is not inserted, the name of the photos has the writing NO_FIX, but they will still be sorted according to the current date and time which are instead acquired via the Jetson Nano internal clock. Each photo taken is finally cataloged in a csv folder, also present inside the USB pen drive.



(a) **(b)**

Figure 3. Preliminary photo acquisition system. In (**a**), there are the Jetson dwarf (A), the converter (B), the screen (C), and the GPS (D); in (**b**), there is the RGBD camera (E) on the front of the trolley at 47 cm high.

The photos were taken by setting the time lapse function to 1 s and in equal numbers in both halves of the football pitch. At the end of the photo acquisition, the images were selected according to image quality.

The dataset is made up of three classes divided into *Cynodon* spp., *Trifolium* spp., and different weed species, which have been cataloged in the unique class of "weed". The class of weeds is made up of species typical of the Mediterranean area. The main botanical genera were *Bellis* spp., *Plantago* spp., *Geranium* spp., *Cirsium* spp., and *Stellaria* spp., and the main types of habitus in terms of species abundance were the rosette and the creeping one (Table 2).

Table 2. Main characteristics of the weed flora present in the soccer pitch [30,31].

	Family	Biological Form	Type	Leaves	Leaves Color	Reproduction
Bellis spp.	*Asteraceae*	Hemicryptophytes	Rosette	Spoon-shaped	Green	Seeds, basal buds
Plantago spp.	*Plantaginaceae*	Hemicryptophytes	Rosette	Broadly lance to egg-shaped leaves with an acute apex	Green	Seeds, basal buds
Geranium spp.	*Geranianceae*	Therophytes	Creeping	Petiolate, palmate-partite	Green	Seeds
Cirsium spp.	*Asteraceae*	Geophytes	Rosette/erect	Spiny and serrated leaves	Dark green	Seeds, rhizome
Stellaria spp.	*Caryophyllaceae*	Therophytes	Creeping	Oval-ovate to broadly elliptic	Pale green	Seeds

The photos were taken in the same parts of the soccer pitch for the respective type management, i.e., the areas subject to the most traffic in the playing area (the same area mentioned in Section 2.2 according to Miller et al. [6]), to evaluate plant distribution after the cutting activity, and the areas behind the two goals to monitor the plants' growth without frequent cutting activity.

2.3.2. Test Dataset and Metrics

A dataset, comprehending turfgrass species and weeds, was used to evaluate the segmentation task performance using YOLOv8s and YOLOv8n. YOLOv8 was launched by Ultralytics in May 2023. YOLO is a single shot detector (SSD) which was first released in 2015. Among the five scaled versions of YOLOv8 (nano, small, medium, large, and extra-large), the small and nano ones were chosen. These models were selected to have a high processing speed. According to Yang et al. [32], this aspect is fundamental for real-time weed detection and treatment, because the actuator would have only a few seconds between the images processing and weed removal.

The dataset was made up of 735 photos containing both turfgrass species and weed annotations. The Google Colaboratory Platform was used to train the selected YOLO models. One 12 GB NVIDIA Tesla K80 GPU is given away for free by Colab, a cloud-based service built on Jupyter notebooks. Models were trained with a batch size of 16 and for 100 epochs. The resolution of the images was adjusted with pre-processing processes of auto-orientation and resizing (stretch to 640 $\times$ 640). To increase the training success, the dataset was expanded (2205 total images) with the following augmentation processes: horizontal and vertical flipping, mosaic, rotation ($-15°$ and $+15°$), hue ($-50°$ and $+50°$), saturation (-50% and $+50\%$), and noise (10% of pixels). A 3-fold cross-validation was performed obtaining 3 different equal parts (Fold1–Fold 3, with one-fold to create test set and two folds to form the training test). This methodology was used to avoid the problem of overfitting and to have a more complete evaluation of the algorithms used [33].

Precision and recall were used to assess the model performances. The precision was calculated as the ratio between True Positive and the sum of True Positive and False Positive; the Recall was calculated as the ratio between True Positive and the sum of True Positive and False Negative. The precision–recall curve is identified as the average precision, which consists of a number between 0 and 1, averaging the average precision for each class, and the mean average precision is calculated. The mean average precision gives information about the model performances. Two different thresholds were adopted, the first one with a confidence score between 0 and 0.5 (mAP_0.5) and the second one with a confidence score between 0.5 and 0.95 (mAP_0.5:0.95). The mean with the abovementioned confidence scores is referred to as the mean of the average precision.

2.4. Statistical Analysis

The visual parameters of color and quality and the measured values of surface hardness and height were analyzed with analysis of variance (ANOVA). The same analysis was conducted to evaluate the percentage of empty and covered zones by herbaceous species. Further analysis through the analysis of variance was conducted to evaluate the presence of turfgrass (bermudagrass and clover) and weeds in different zones within the two soccer pitch halves. Analysis of variance was also conducted to evaluate the primary energy consumption of the two machines employed. One-way ANOVA was conducted to evaluate the soccer pitch users' evaluation of turfgrass in function of the type of management. The Shapiro–Wilk test was used to settle the data normality, and the Bartlett test was used for homoscedasticity. The data were transformed with a square root transformation, when necessary, to respect the normality assumption. The least significant difference (LSD) test at 0.05 of probability was conducted with the package "agricolae".

The data regarding YOLOv8s and YOLOv8n performances were analyzed with multivariate analysis of variance (MANOVA), adopting the following independent variables in the model: the YOLO version (YOLOv8s and YOLOv8n), box/mask, the class (all, *Cynodon* spp., *Trifolium* spp., and weed), and their interaction. Their effects were analyzed on the dependent variables, the YOLOv8s and YoloV8n performances: precision, recall, mAP_0.5, and mAP_0.5:0.95. Data were analyzed using the statistical software SPSS (IBM Corp. Released 2019, Version 26.0. Armonk, NY, USA: IBM Corp.). Wilks' lambda, Pillai's trace, Hotelling's trace, and Roy's largest root were calculated to assess how the model terms contribute to the overall covariance. At the beginning, a complete factorial analysis was conducted, and then a simplified model was adopted, excluding everything that was not significant from the complete factor analysis.

3. Results

3.1. Turfgrass Quality, Performances, and Composition

The analysis of variance revealed that the type of management had a significant effect on the surface hardness. The position in the soccer pitch had a significant effect on turfgrass color and surface hardness. Their interaction had a significant effect on the surface hardness (Table 3). The mean value of surface hardness in the function of the management and position revealed how the surface hardness increased much more in the central zone mowed by the ride-on mower (Figure 4).

Table 3. Results of the two-way ANOVA analysis evaluating the effect of management, position, and their interaction on color, quality, and surface hardness of the turfgrass.

Source	Color	Quality	Surface Hardness
Management	ns	ns	***
Position	**	ns	***
Management × Position	ns	.	***
LSD			1.71

$p < 0.001$ "***"; $p < 0.01$ "**"; $p < 0.1$ "."; ns: not significant.

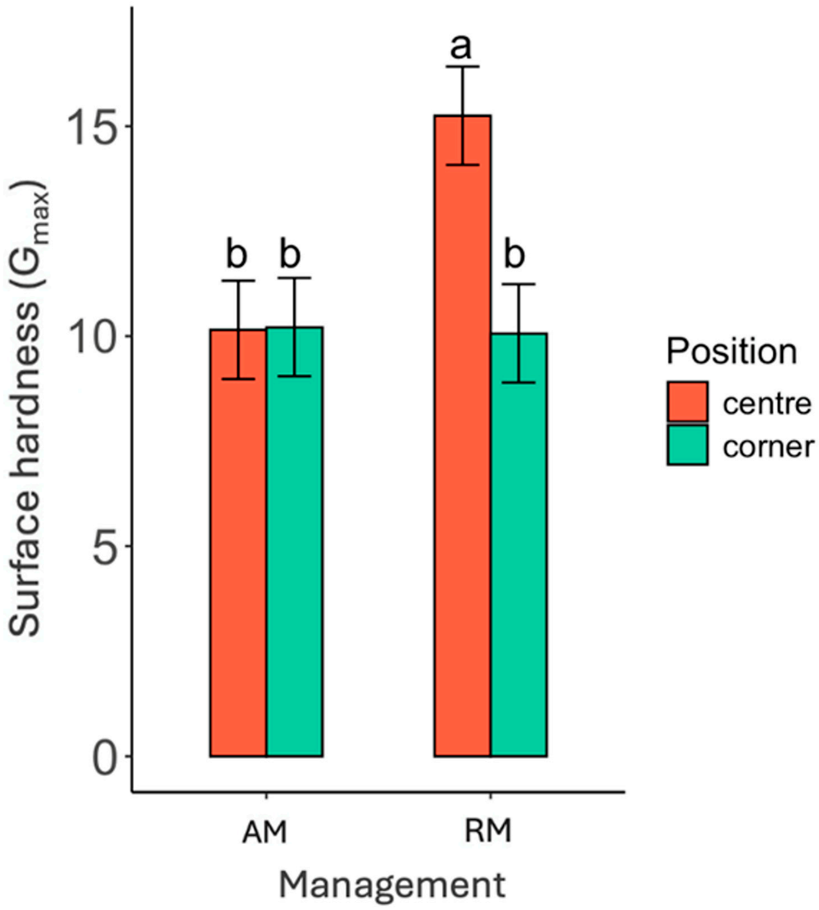


Figure 4. Effect of the interaction between management (autonomous mower (AM) and ride-on mower (RM)) and position on the surface hardness. Means denoted by different letters indicate statistically significant differences at $p < 0.05$ (LSD test). LCL (Lower Confidence Limit) and UCL (Upper Confidence Limit) are reported.

To complete the results obtained from the statistical analysis, the average values of the volumetric water content (VWC), the electrical conductivity (EC), and the temperature of the soil obtained through TDR measurements in the corner and central zones for the two different types of management are reported in Table 4.

Table 4. Recorded values of the TDR measurements.

Zone	Autonomous Mower			Ride-On Mower		
	VWC %	mS·cm^{-1}	°C	VMC %	mS·cm^{-1}	°C
Centre	38.2	0.16	11.7	36.5	0.31	14
Corner	37.9	0.25	13.4	39.5	0.17	11.8

The analysis of variance revealed that the type of management and the position within the soccer pitch had a significant effect on the turfgrass height. The interaction between the type of management and the position had a very low significance, the p-value is lower than 0.1 (Table 5).

The analysis of variance revealed that the type of management had a significant effect on the coverage, the empty areas, and weed percentage. The position within the soccer pitch had a significant effect only on weeds compared to the interaction between the type of management and position (Table 6). The mean value of weed percentage in the function of type of management and position revealed how weed percentage increased much more in the corner zones managed by the robot mower (Figure 5).

Table 5. Results of the two-way ANOVA analysis evaluating the effect of management, position, and their interaction on the turfgrass height.

Source	Height
Management	***
Position	***
Management × Zone	.

$p < 0.001$ "***"; $p < 0.1$ ".": not significant.

Table 6. Results of the two-way ANOVA analysis evaluating the effect of management, position, and their interaction on coverage, empty zones, and weed percentage and the turfgrass species percentage.

Source	Coverage	Empty	Weeds	Turfgrass
Management	*	*	**	.
Position	ns	ns	***	ns
Management × Position	ns	ns	**	ns
LSD			4.078	

$p < 0.001$ "***"; $p < 0.01$ "**"; $p < 0.05$ "*"; $p < 0.1$ "."; ns: not significant.

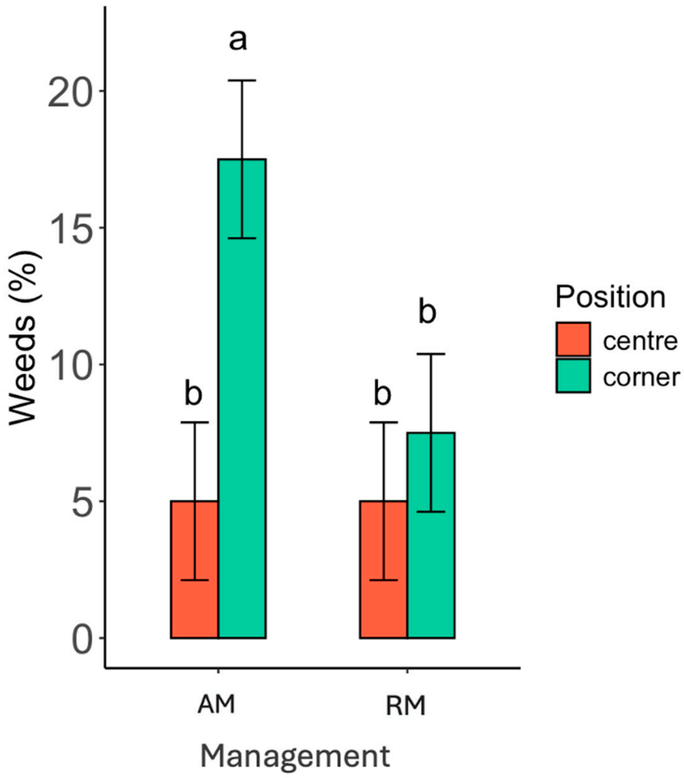


Figure 5. Effect of the interaction between management (autonomous mower (AM) and ride-on mower (RM)) and position on the weed percentage. Means denoted by different letters indicate statistically significant differences at $p < 0.05$ (LSD test). LCL (Lower Confidence Limit) and UCL (Upper Confidence Limit) are reported.

Survey Answers

In Table 7, all the answers and the judgments of the turfgrass quality and performance parameters are reported.

Table 7. Results of the surveys about turfgrass quality and performance parameters.

Questions	Answers									
Have you noticed a difference between the two-mowing management?	Yes	Yes	Yes	Yes	Yes					
Did the robot presence disturb matches and training sessions?	No	No	No	No	No					
Have you noticed any different mechanical abrasion?	No	No	No	No	No					
Quality parameters	Autonomous mower					Ride-on mower				
Color	Medium	High	High	High	High	Low	Medium	Medium	Medium	Medium
Density	High	High	High	Medium	Medium	Medium	Medium	Medium	Low	Low
Uniformity	High	High	High	High	High	Low	Medium	High	Medium	Medium
Performances parameters	Autonomous mower					Ride-on mower				
Traction	High	No answer	High	Medium	Medium	Medium	No answer	Low	Low	Medium
Hardness	High	High	High	Medium	Medium	High	High	Low	Low	Medium
Slipperiness	High	Medium	High	Medium	Medium	Medium	Medium	Medium	Low	Low
Athlete–surface interaction	High	High	high	Medium	Medium	Low	High	Medium	Medium	Medium
Ball–surface interaction	High	Medium	High	High	High	Low	Medium	Medium	Medium	Medium

High: 9; medium: 4.5; low: 1. To evaluate the survey answers, one-way ANOVA was conducted for each parameter indagated (Table 8). The analysis revealed that the type of management has a significative effect on the parameter evaluation only for color, uniformity, ball–surface interaction, and density. The mean value of the parameter evaluation in the function of type of management is reported in Figure 6.

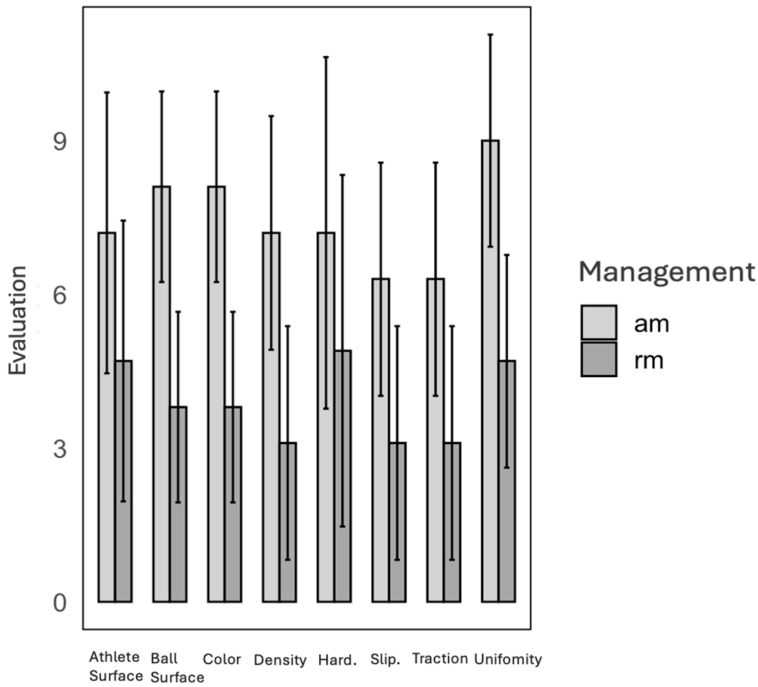


Figure 6. Mean value of turfgrass parameter evaluation in function of the type of management. LCL (Lower Confidence Limit) and UCL (Upper Confidence Limit) are reported. Parameters indagated: athlete–surface interaction (athlete surface), ball surface (ball–surface interaction), color, density, hardness (Hard.), slipperiness (Slip.), traction, and uniformity.

Table 8. Result of the one-way ANOVA evaluating the effect of the management type on the football pitch users' evaluation.

Source	Athlete Surface	Ball Surface	Color	Density	Hardness	Slipperiness	Traction	Uniformity
Management	NS	**	**	*	NS	.	.	**

$p < 0.01$ "**"; $p < 0.05$ "*"; $p < 0.1$ "."; NS: not significant.

3.2. Energy Consumption of Mowing Systems

The respective energy consumption of the autonomous mower and ride-on mower is reported in Table 9. The autonomous mower operational time to mow half a field was averaged through different measurements obtaining the value of 51.1 h·week^{-1}. Electric energy consumption was 1.8 kWh·week^{-1}. The primary energy consumption estimated as the energy from primary sources transformed into electric energy corresponds to 3.49 kWh·week^{-1}. The ride-on mower operated twice a week, covering 2600 m^2, which was the same area covered by the autonomous mower. It worked 1 h·week^{-1} at an average working speed of 0.1 km·h^1. Gasoline consumption was 1.98 kg·week^{-1}, and the primary energy consumption corresponds to 24.27 kWh·week^{-1}. As evident from these results, the autonomous mower had a longer working time to cover the same area, but the primary energy consumption was extremely lower. Analysis of variance revealed that the type on management ($p < 0.001$) had a significant effect on primary energy consumption. The AM allowed a percentage decrease in primary energy of 85.6%.

Table 9. Operative performances of the cutting systems.

Parameter	Unit	Value
Autonomous mower		
Daily mowing time	h day $^{-1}$	7.3
Electric energy consumption per week	kWh·week^{-1}	1.8
Primary energy consumption per week	kWh·week^{-1}	3.49
Ride-on mower		
Total operative time	h·week^{-1}	1.00
Gasoline consumption	kg·week^{-1}	1.98
Primary energy consumption per week	kWh·week^{-1}	24.27

3.3. YOLOv8 Results

Results for YOLOv8s and YOLOv8n Models

Table 10 shows the training results of the YOLOv8s and YOLOv8n semantic segmentation algorithms for detecting and segmenting main crops (*Cynodon* spp. and *Trifolium* spp.) and weeds. These results refer to the mean and standard deviation of the models' performance on the 3-fold cross-validation. The results include performance metrics for precision, recall, mAP_0.5, and mAP_0.5:0.95 for both box and mask detection. Each value is accompanied by its standard deviation, indicating the variability in performance across different folds. For all classes, YOLOv8s demonstrates an average precision of 0.700 $\pm$ 0.105 and a recall of 0.603 $\pm$ 0.097 for box detection, with a mAP_0.5 of 0.668 $\pm$ 0.143 and mAP_0.5:0.95 of 0.408 $\pm$ 0.119. For mask detection, the model shows an average precision of 0.696 $\pm$ 0.102 and a recall of 0.585 $\pm$ 0.099, with a mAP_0.5 of 0.643 $\pm$ 0.145 and mAP_0.5:0.95 of 0.298 $\pm$ 0.082. The high standard deviations suggest significant variability across the different folds. Analyzing individual classes of weeds achieved the best overall results.

Table 10. Results of three-fold cross-validation test of YOLOv8s and YOLOV8n models.

YOLOv8s								
Class	Box				Mask			
	Precision	Recall	mAP_0.5	mAP_0.5:0.95	Precision	Recall	mAP_0.5	mAP_0.5:0.95
All	0.700 ± 0.105	0.603 ± 0.097	0.668 ± 0.143	0.408 ± 0.119	0.696 ± 0.102	0.585 ± 0.099	0.643 ± 0.145	0.298 ± 0.082
Cynodon spp.	0.654 ± 0.091	0.651 ± 0.107	0.684 ± 0.138	0.429 ± 0.122	0.647 ± 0.091	0.627 ± 0.111	0.651 ± 0.145	0.303 ± 0.083
Trifolium spp.	0.699 ± 0.130	0.500 ± 0.084	0.585 ± 0.150	0.347 ± 0.114	0.689 ± 0.123	0.484 ± 0.084	0.561 ± 0.144	0.246 ± 0.075
Weeds	0.755 ± 0.096	0.658 ± 0.112	0.735 ± 0.143	0.447 ± 0.121	0.753 ± 0.095	0.645 ± 0.11	0.717 ± 0.147	0.344 ± 0.090
YOLOv8n								
Class	Box				Mask			
	Precision	Recall	mAP_0.5	mAP_0.5:0.95	Precision	Recall	mAP_0.5	mAP_0.5:0.95
All	0.599 ± 0.064	0.506 ± 0.059	0.545 ± 0.085	0.302 ± 0.065	0.591 ± 0.069	0.493 ± 0.251	0.523 ± 0.087	0.231 ± 0.047
Cynodon spp.	0.570 ± 0.050	0.560 ± 0.070	0.570 ± 0.070	0.330 ± 0.060	0.560 ± 0.050	0.530 ± 0.270	0.540 ± 0.080	0.240 ± 0.050
Trifolium spp.	0.580 ± 0.103	0.379 ± 0.051	0.434 ± 0.078	0.233 ± 0.060	0.574 ± 0.105	0.370 ± 0.189	0.412 ± 0.076	0.174 ± 0.040
Weeds	0.642 ± 0.086	0.584 ± 0.100	0.628 ± 0.104	0.346 ± 0.076	0.640 ± 0.088	0.574 ± 0.299	0.614 ± 0.105	0.277 ± 0.060

For all classes, YOLOv8n had an average precision of 0.599 ± 0.064 and a recall of 0.506 ± 0.059 for box detection, with a mAP_0.5 of 0.545 ± 0.085 and mAP_0.5:0.95 of 0.302 ± 0.065. The lower standard deviations compared to YOLOv8s indicate more stable performance. For mask detection, the model shows an average precision of 0.591 ± 0.069 and a recall of 0.493 ± 0.251, with a mAP_0.5 of 0.523 ± 0.087 and mAP_0.5:0.95 of 0.231 ± 0.047. Similar to YOLOv8s, weeds achieved the best overall performance. The higher overall performance metrics of YOLOv8s compared to YOLOv8n are also characterized by higher standard deviation values, indicating greater instability. In addition, YOLOv8s (102.4 ms) was demonstrated to be slower than YOLOV8n (45.9 ms).

The multivariate analysis of variance conducted on the performance parameters revealed significant differences ($p < 0.001$) between YOLO versions for every performance parameter, box and mask revealed significant differences for mAP_0.5 ($p < 0.05$) and mAP_0.5:0.95 ($p < 0.001$), class revealed significant differences ($p < 0.001$) for every performance parameter (Table 11). A significant difference was obtained from the interaction between the YOLO version (YOLOv) and box/mask for the mAP_0.5:0.95 ($p < 0.05$). From Tables 12 and 13, it is evident that higher mean values of performances were obtained with YOLOv8s and for the box, respectively.

Table 11. Mean square, F-value, and p-value of MANOVA conducted on YOLO performances.

Source	**Performance**	**Mean Square**	**F**	***p***
YOLOv	Precision	0.127	94.954	***
	Recall	0.108	78.083	***
	mAP_0.5	0.178	178.413	***
	mAP_0.5:0.95	0.09	122.994	***
Box/Mask	Precision	2.803×10^{-4}	0.210	0.649
	Recall	0.003	2.093	0.156
	mAP_0.5	0.007	6.818	*
	mAP_0.5:0.95	0.099	135.881	***
Class	Precision	0.017	12.440	***
	Recall	0.079	57.087	***
	mAP_0.5	0.064	63.896	***
	mAP_0.5:0.95	0.023	31.351	***
YOLOv × Box/Mask	Precision	6.075×10^{-5}	0.046	0.832
	Recall	5.633×10^{-5}	0.041	0.841
	mAP_0.5	9.188×10^{-6}	0.009	0.924
	mAP_0.5:0.95	0.005	6.391	*

$p < 0.001$ "***"; $p < 0.05$ "*".

Table 12. Comparison between the average values of performances in the two versions of YOLO.

Performance	YOLOv	Mean	Std Error	95% Confidence Interval	
				Lower Limit	Upper Limit
Precision	8n	0.595	0.007	0.58	0.61
	8s	0.698	0.007	0.683	0.713
Recall	8n	0.499	0.008	0.484	0.515
	8s	0.594	0.008	0.579	0.609
mAP_0.5	8n	0.534	0.006	0.521	0.547
	8s	0.656	0.006	0.643	0.669
mAP_0.5:0.95	8n	0.266	0.006	0.255	0.278
	8s	0.353	0.006	0.342	0.364

8n – YOLO version 8n; 8s – YOLO version 8s.

Table 13. Comparison between the average values of YOLO performances of box and mask.

Performance	Box/Mask	Mean	Std Error	95% Confidence Interval	
				Lower Limit	Upper Limit
Precision	Box	0.649	0.007	0.634	0.664
	Mask	0.644	0.007	0.629	0.659
Recall	Box	0.555	0.008	0.539	0.570
	Mask	0.539	0.008	0.524	0.554
mAP_0.5	Box	0.607	0.006	0.594	0.620
	Mask	0.583	0.006	0.570	0.596
mAP_0.5:0.95	Box	0.355	0.006	0.344	0.366
	Mask	0.264	0.006	0.253	0.275

From Table 14, it is evident how weeds obtained the highest performance parameters for precision and mAP_0.5. Regarding recall and mAP_0.5:0.95, the weed class showed no differences compared to the *Cynodon* spp. class.

Table 14. Comparison between the average values of YOLO performances in 4 different classes.

Performance	Class	Mean [1]	Std Error	95% Confidence Interval	
				Lower Limit	Upper Limit
Precision	All	0.647 b	0.011	0.625	0.668
	Cynodon spp.	0.609 b	0.011	0.588	0.631
	Trifolium spp.	0.633 b	0.011	0.612	0.655
	Weed	0.697a	0.011	0.676	0.719
Recall	All	0.547 b	0.011	0.525	0.568
	Cynodon spp.	0.592 a	0.011	0.570	0.614
	Trifolium spp.	0.433 c	0.011	0.411	0.455
	Weed	0.615 a	0.011	0.593	0.637
mAP_0.5	All	0.595 b	0.009	0.576	0.613
	Cynodon spp.	0.612 b	0.009	0.594	0.631
	Trifolium spp.	0.498 c	0.009	0.480	0.517
	Weed	0.674 a	0.009	0.656	0.692
mAP_0.5:0.95	All	0.310 b	0.008	0.294	0.326
	Cynodon spp.	0.325 ab	0.008	0.309	0.341
	Trifolium spp.	0.250 c	0.008	0.234	0.266
	Weed	0.354 a	0.008	0.338	0.370

[1] Means denoted by different letters indicate statistically significant differences.

The interaction between the two different YOLO versions and box/mask obtained higher mean values for the box in both cases, with the highest value (0.408) for the box of YOLOv8s (Table 15).

Table 15. Mean value of mAP_0.5:0.95 in the interaction between YOLOv and box/mask.

Performance	YOLOv	Box/Mask	Mean	Std. Error	95% Confidence Interval	
					Lower Limit	Lower Limit
mAP_0.5:0.95	8n	Box	0.302	0.008	0.286	0.318
		Mask	0.231	0.008	0.215	0.247
	8s	Box	0.408	0.008	0.392	0.424
		Mask	0.298	0.008	0.282	0.313

8n – YOLO version 8n; 8s – YOLO version 8s.

4. Discussion

Mowing Activity Effect on Turgrass Quality and Performance

The analysis of the cutting activity of two different mowing systems, a ride-on mower and an autonomous mower with systematic trajectories, did not give significant results in terms of quality, but the position demonstrated to have an effect on the color rate. These results could be directly correlated to the height results; the value of height was strongly affected by the type of management and the position, even if their correlation did not give significant results. The mean color value was higher in the corner position (5.36) with respect to the central one (3.69), and these results are in line with the height one. In fact, the height measures correspond to 2.99 in the corner and 2.52 in the central zone. This value can indicate the higher value of color, because of the presence of major green mass. This result is in line with [34], which highlights how the lower mowing height significantly affects the loss of green cover. In addition, according to Youngner et al. [35], lower heights can result in reduced traffic tolerance. According to Luglio et al. [13], the trampling level of the cutting activity can affect the quality parameters of turfgrass. At this stage, it is useful to underline the surface hardness results; this parameter is significantly affected by management, position, and their interaction. The soil hardness increased significantly in the central position (15.25 G_{max}) mowed by the ride-on mower with respect to the corner position managed in the same way, which together with the specular zones mowed by the autonomous mower have an overall mean value of 10.14 G_{max}. The lower color results in the central area could be explained by the surface hardness; in fact, the soil compaction in the first cm of soils due to the action of machine weight can have a strong effect on the turf quality because the plant shoots become less dense and more susceptible to direct and indirect temperature stress [12,36].

The results of the turfgrass composition show the slight effect of the type of management on the coverage and the empty space. The area mowed by the robot mower had a coverage percentage of 97% compared to the other one, which had 70% coverage. This result directly influenced the weed results. According to Pirchio et al. [37], autonomous mowing can increase the percentage of weed cover. However, it is important to underline the different types of weed species, which influenced this finding; the creeper-type plants favor a constant mowing height [37]. In the soccer pitch analyzed, most of the weeds do not have the creeper habitus, so they should have been affected by the autonomous mower's constant mowing activity according to the results of Pirchio et al. [37] on Manila grass. The major incidence of weeds in the half mowed by the robot mower is also directly connected to the coverage percentage cited before and to the major percentage of empty space in the half mowed by the ride-on mower (29.5% vs. 2.5% of empty space in the half mowed by the autonomous mower). This substantial lack of green cover in the half cut by the ride-on mower makes it difficult to have a real comparison on the actual incidence of weeds. These results could also be linked to the results on the surface hardness mentioned above, which makes the growth not only of the turf but also of other plants more difficult. Another aspect which contributes to the major incidence of weeds in the robot mower's half is the low turfgrass height. In fact, in turfgrass mowing with less frequency, weeds have to grow taller to survive, and when they grow above the mowing height, they become easier to cut.

The answers collected through the survey are not generally in accordance with the statistical analysis results. This could be explained by the people's perception of the autonomous mower's cutting work. Pedersen et al.'s [38] findings highlight that autonomous systems demonstrate more flexibility than the conventional cutting machine, and they may be able to reduce the labor costs and the number of daily working hours in a significant way. The survey results may be also connected to the many perceived advantages provided by autonomous mowers such as saving human labor and preventing exposure to dust, allergens, and potential injury [39]. The results from Pedersen et al. [38] also demonstrate that one of the major concerns was the repetitiveness of the operation and the dependence on the climatic conditions; these aspects can be easily avoided through automatic cutting machines. In light of all these aspects, it can be hypothesized that the results of the survey were guided by these common perceptions of users.

The findings about energy consumption align with the previous literature, which has already observed the reduction in primary energy consumption using autonomous mowers, and they are also in line with the global need to reduce the environmental footprint of many activities, including lawn maintenance. According to Pirchio et al. [37], the adoption of electric power machines, such as the autonomous mower, can contribute to mitigating the environmental impact of garden equipment, with lower global warming potential. The daily mowing time results align with Pirchio et al.'s [37] findings, and the weekly management of an autonomous mower is longer than the conventional cutting system, but the energy consumption is lower. This could be due to the optimal robot path planning and to the lower autonomous mower power requirements.

The working efficiency in terms of weekly working time (51.1 *h*) can increase through the adoption of a larger working width [17]. This overall lower energy consumption is also due to the lower power consumption (0.035 kWh$\cdot$h^{-1}) needed to perform cutting activity; in addition, the small amount of grass to cut everyday affects the power consumption amount. Cutting every day, it only cuts small clippings [13,23]. The integration of an innovative approach for monitoring green areas represents a promising way for enhancing their management and conservation. This approach studied by Angelini et al. [40] as a natural intelligence approach for monitoring habitats is based on different information about environmental status, comparing them to a reference status. In the specific case of our study, the key aspect of the turfgrass ecosystem in sports fields is the qualitative and performance parameters. These two aspects are strongly correlated to the weed encroachment within the turfgrass. According to Luglio et al. [13], the presence of weeds is correlated to a functional quality and aesthetic perception loss. The estimated vegetation cover, as one of the parameters considered to evaluate turf composition, could be considered a key indicator of conservation status. This estimation is usually conducted on the field, distinguishing main crop species from the different weeds, which sometimes can be very similar to each other, requiring a skilled plant scientist [40]. For this reason, different experiments could be carried out to automate the monitoring of habitats, such as the turfgrass one. The experiment conducted with YOLOv8s and YOLOv8n, assuming hypothetically that the number of instances may coincide with the number of turfgrass species and weeds in the soccer pitch, had the main scope of moving the first steps towards the creation of distribution mapping to understand if weed management interventions are necessary. The training results demonstrate how the average precision of segmentation is inversely proportional to the inference speed. The major inference speed of YOLOv8n results in a lower value of metrics results; however, they have proven to have greater stability thanks to standard deviation values that are generally lower than those of YOLOv8s. In this regard, Sampurno et al. [41] assessed the efficiency and accuracy of YOLOv8n-seg in recognizing the uncut weeds within tree rows with different herbaceous species. From the statistical analysis, it is evident how the two different YOLO versions and the types of plant (class) are the most significant factors for all analyzed parameters. In particular, YOLOv8s was confirmed to have higher mean values. In addition, the data in Table 14 confirmed the highest mean values for the weed class; these results are in accordance with Sampurno et al. [41], which confirm the potential of YOLOv8-based weed detection.

5. Conclusions

This trial highlights the impact of two different cutting systems—ride-on mower and autonomous mower—on a football field.

A higher value of average height was detected in the half mowed by the ride-on mower (2.95 cm) compared to the one mowed by the autonomous mover (2.60 cm). In terms of surface hardness, the central zone showed notable variation: 15.25 Gmax for the ride-on mower versus 10.15 Gmax for the autonomous mower. These findings suggest that the autonomous mower effectively maintains the turfgrass height constant at around 25 mm and with a higher percentage of coverage (97.5%); it has a minor effect on the surface hardness in the central zone, which is a fundamental aspect both for the plants' growth and the playability. However, the autonomous mower activity was associated with a higher weed incidence in the corner zones (17.5%) compared to the ride-on mower (7.5%). Weed coverage remains a significant challenge, particularly in high-level sports contexts, but in lower-level contexts this can be managed with less rigor based on the extent of their coverage.

Monitoring the floristic composition of turfgrass is essential, and automating this process could be beneficial. YOLOv8s performed better for weed detection. Future studies should explore playability differences between the two cutting systems and further investigate YOLO's effectiveness by testing new versions and adjusting parameters like epochs and image quantities to further evaluate the performance of the model in the segmentation of weeds within green plant cover, such as turfgrass.

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