MACHINE LEARNING-ENHANCED TURFGRASS LOGISTICS THROUGH REMOTE SENSING

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Abstract

Turfgrass management represents a critical aspect of landscaping, sports fields, and golf course maintenance. The efficient logistics of turfgrass, encompassing tasks such as mowing, fertilization, and irrigation, can significantly impact its health and aesthetics. In recent years, remote sensing technologies and machine learning have emerged as powerful tools for optimizing turfgrass logistics. This work presents a comprehensive study on the application of machine learning algorithms to enhance the management of turfgrass through remote sensing data. The proposed approach leverages various remote sensing techniques, including satellite imagery, unmanned aerial vehicles (UAVs), and ground-based sensors, to gather high-resolution data on turfgrass health, moisture levels, and growth patterns. These data sources feed into a machine learning pipeline, comprising data preprocessing, feature engineering, and algorithm selection, to develop predictive models for turfgrasses. Our findings demonstrate that machine learning models, when trained on remote sensing data, can accurately predict turfgrass parameters that can be used to ensure continuous improvement in turfgrass logistics. The integration of machine learning into turfgrass logistics not only enhances resource utilization but also reduces environmental impact by minimizing unnecessary inputs. We present case studies from various landscapes, including sports fields and golf courses showcasing the practicality and adaptability of our approach.

Keywords: Turfgrass logistics, vegetation indices, machine learning, deep learning, remote sensing

1. INTRODUCTION

Integration of machine learning methods and remote sensing technology marks a major transformation in agricultural logistics, particularly in the field of grass-cover management. The application of these techniques addresses a wide range of challenges in turfgrass logistics, including resource allocation optimization, precision farming, and sustainability. This paper presents a new approach to revolutionizing turfgrass management by leveraging machine learning and remote sensing.

Turfgrass is an essential component of residential and commercial landscapes, sports fields, and public spaces, requiring a high level of attention and precision in cultivation and maintenance. Traditional management methods for turfgrass logistics are labor-intensive and often rely on experience rather than data-based strategies. Remote sensing technologies such as satellite images and unmanned aerial vehicles (UAVs) provide extensive spatial and temporal data that have not been used until recently due to the complexity of their integration into practical applications. In this paper, we took an opportunity to apply machine learning methodologies and propose a framework that allows it to learn from data and furthermore, offers an unprecedented opportunity to analyze and interpret the remote sensing data sets. Such a strategy allows for predictive modeling enabling more efficient and effective management of turfgrass logistics. The introduction of artificial intelligence into turfgrass management can lead to improvements in irrigation, fertilization, pest control, and harvesting schedules, thereby optimizing the supply chain, and reducing environmental impact.

This paper explores the latest advances in machine learning (ML) algorithms for the processing and analysis of remote sensing data. We investigate the potential of ML to improve the precision of turfgrass cultivation by predicting the general aspect, uniformity of turfgrass, leaf color and slenderness. In addition, we inspect a possibility of turfgrass mineral content estimation based on multispectral imagery. We also discuss the practical implications of applying these technologies in real-world environments, the challenges, and limitations to be faced, and the future direction of improved turfgrass logistics using machine learning.

By demonstrating how ML can extract meaningful insights from remotely sensed data, this paper aims to provide a comprehensive overview of machine learning applications in turfgrass logistics and to offer a roadmap for future research and implementation in this field. Through this exploration, we underscore the importance of integrating innovative technologies to sustainably meet the growing demand for high-quality turfgrass in an era of limited natural resources and environmental change.

2. MATERIALS AND METHODS

Multispectral imagery is a powerful and versatile technology that captures data across multiple distinct bands or wavelengths of the electromagnetic spectrum. Unlike traditional single-band or panchromatic imagery, each band of multispectral imagery provides unique information about the surface or objects being observed, allowing for a more comprehensive analysis of the environment [1]. By combining data from multiple spectral bands, multispectral imagery enables us to discriminate between different surface materials, detect changes over time, assess vegetation health, and identify mineral content with good precision. In this section, we depict our research methodology, which played an essential role in achieving accurate and efficient classification of turfgrass using multispectral imagery and machine learning techniques.

2.1 MULTISPECTRAL IMAGERY DATABASE

The database used in this research uses multispectral imagery data obtained from digital drone cameras. Dataset was collected during a long-term experiment performed by agricultural and teledetection scientists. Field experiments were carried out over two vegetation cycles at the Experimental Station of the University of Agriculture in Krakow from 2021 to 2022. Five grass mixtures were sown on 80 experimental fields, which were subsequently divided into extensive and intensive parts. The former received a more intensive supplementation process and more frequent mowing, following the maintenance guidelines provided by COBORU (Research Centre for Cultivar Testing). Weather conditions during the experimental period favored sustainable grass growth, with average air temperatures ranging between 15.3 and 16°C throughout the vegetation months (April–September). Additionally, the average rainfall levels were approximately 300–400 mm in 2020 and 2022, with higher values of around 600mm recorded in 2021. During prolonged drought periods, the intensive fields were systematically watered every 3 days. The UAV images were gathered weekly with a standard RGB camera and a multispectral camera covering ten bands of the light spectrum: 1) Blue 475 nm, 2) Green 560 nm, 3) Red 668 nm, 4) Red Edge 717 nm, 5) Near Infrared 842 nm, 6) Blue 444 nm, 7) Green 531 nm, 8) Red 650 nm, 9) Red Edge 705 nm, 10) Red Edge 740 nm. Each flight session included a detailed assessment of each research field by experts, focusing on the general aspect, leaf color, slenderness, and uniformity of turfgrass, each rated on a 1–9 scale. At the same time, three primary in-situ measurements were taken using ground-based sensors: NDVI, LAI, and SPAD, providing a multifaceted understanding of the turfgrass's health and development. For a more comprehensive understanding of the turfgrass's health and the environmental conditions affecting it, auxiliary measurements like moisture level, dry biomass, and wet biomass were also included. Each month, laboratory analysis was conducted on probes collected from each experimental field to estimate both micro- and macroelements, adhering to the AOAC (2006) Method [2]. This rigorous approach allowed for a detailed understanding of the nutrient composition through the determination of nitrogen (N), phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), sodium (Na), manganese (Mn), iron (Fe), zinc (Zn), and copper (Cu) content.

During the experiment, drone flights sessions were precisely coordinated to occur on the same days as the in-situ and laboratory measurements. This alignment ensured consistency in data collection across different methodologies. In the first year, a total of 5171 images were collected, each cropped to single experimental field. In the second year, the number of images collected was 1625. This systematic approach allowed for a detailed and time-aligned comparison of visual, in-situ, and laboratory data. The data collection process involved expert evaluation of visual aspects of the turf as well as in-situ and laboratory measurements. Such data is more suitable for regression tasks in machine learning (ML) algorithms, as it involves predicting a continuous output, like nutrient levels or plant health indices, based on the observed measurements. In **Table 1**, we gathered the number of collected measurements.

Table 1 Number of collected images

	Visual evaluation		In-situ measurements			LABoratory
	general aspect and uniformity of turfgrass	leaf color and slenderness	SPAD	NDVI	LAI	
2021	1980	1760	1968	3926	3220	1780
2022	3124	2872	1221	1784	1703	1631
total	4104	2632	3189	5710	4923	3411

2.2 MACHINE LEARNING FRAMEWORK FOR TURFGRASS ANALYSIS

In this paper, we aim to analyze a machine learning (ML) framework tailored for the analysis of turfgrass logistics. This framework stands at the intersection of advanced data analytics and practical turf management, aiming to streamline and enhance the logistical aspects of turfgrass care. By integrating data from expert evaluations, in-situ and laboratory measurements, and UAV imagery, the framework is designed to, in the future, help optimize resource allocation, maintenance schedules, and treatment applications. The core goal is to employ ML algorithms to uncover insights and patterns that are able to evaluate visual drone imagery to evaluate the visual turf aspect as well as predict the in-situ and mineral content of the turfgrass area. Such a procedure can then be used for more efficient and effective turfgrass logistics strategies. This approach not only represents a novel application of ML in turf management but also can change the way turfgrass logistics are approached, leading to more sustainable and cost-effective practices.

The use of machine learning in UAV remote sensing for precision agriculture is a rapidly evolving field, with a focus on feature extraction and model performance [3]. In precision agriculture, UAV remote sensing has shown promise in drought stress, weed and pathogen detection, nutrient status assessment, and yield prediction, with potential for further research in data integration and model development [4]. In the described study, from the vast range of machine learning algorithms available, we selected deep artificial neural networks. In general, deep neural networks have been found to outperform shallow networks in terms of efficiency and function approximation [5–7]. In 2018, Baral *et al.* suggested that the success of deep networks could lie in their parallel structure [5]. Linag and Srikant demonstrated that deep networks require exponentially fewer neurons than shallow networks for the same level of function approximation [6]. Then, in 2020, Bokati *et al.* described a study that supports the efficiency of deep learning, providing a theoretical explanation for its superiority over support vector machines [7]. Together, these studies underscore the importance of the depth and architecture of deep neural networks in enhancing their performance. Furthermore, we investigated deep learning approaches well suited for digital image and signal processing. In literature, one can notice that deep learning methodologies, particularly convolutional neural networks (CNNs), have demonstrated superior performance [8–11]. This is due to their ability to automatically learn and extract relevant features from images [8, 9]. CNN's showed their potential, especially in medical image analysis, where they have shown remarkable success in various tasks including feature representation, detection, segmentation, classification, and prediction [8]. Furthermore, the use of deep neural networks has been shown to improve the speed and quality of 3D image processing, outperforming conventional methods [10]. However, despite their great potential, these techniques depend on large datasets, which can be a limitation in certain applications [11]. In the subjected studies, we have collected a reasonable-sized database that allows us to take advantage of deep learning methodology, leading to the proposition of a framework that is schematically depicted in **Figure 1**.

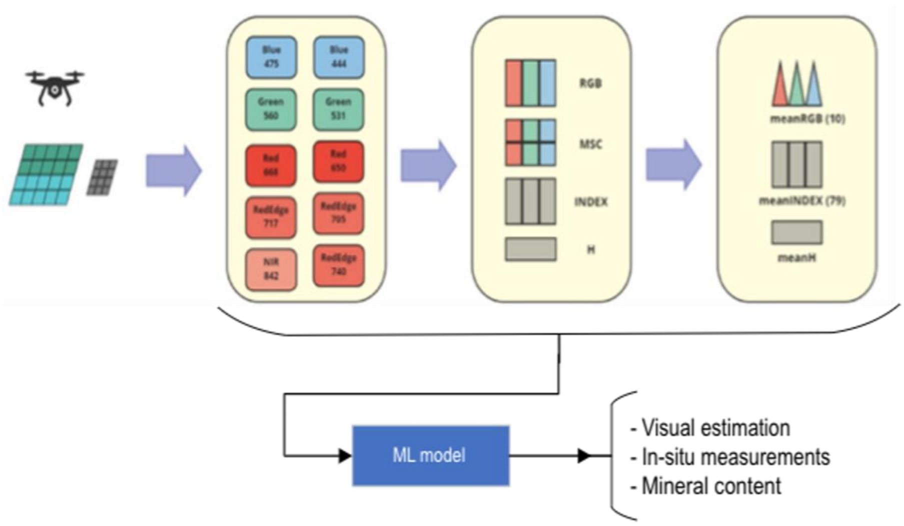

Figure 1 Diagram of a proposed framework

The primary task of assessing turfgrass condition was divided into classification and regression sub-tasks. Classification task was applied for a visual assessment and regression, or parameter estimation was utilized for continuously measured parameters, both in the field and laboratory. After experimenting with various solutions, including popular pre-trained deep neural models, we opted to develop custom convolutional network architectures tailored to our training data's unique nature. Since different amounts of data were available for different parameters, we chose to construct separate classifiers and regressors for each estimated parameter. This decision offered several advantages, including computational efficiency, as these models had low complexity. Additionally, it allowed us to train only the networks for which new data became available. These individual networks did not share their weights, as we found this approach to be more efficient; it was challenging to determine which model performed the best feature extraction. Therefore, each network was trained independently for its specific task. These custom structures take a small patch from the multispectral 10-channel image as their input and extract essential features through convolutional and fully-connected layers for final estimation or classification. Consequently, once a sufficient amount of prepared multispectral imagery of the analyzed surface is collected, one can promptly obtain the model's inference results.

3. RESULTS

In this section, we show the results that were obtained with the application of our deep learning framework to the database collected during our research. These outcomes not only reflect the effectiveness of the employed methodologies but also provide insights into the turfgrass analysis. The data, encompassing both qualitative expert evaluations and quantitative measurements, have been analyzed, revealing patterns and correlations in the data. The described findings are crucial in understanding the broader implications of our study and in guiding future research directions in the field of turfgrass logistics.

In **Table 2**, we gathered the results on automated visual evaluation results for different numbers of classes, and in **Table 3**, we provided correlations between machine learning models and real measurements. From **Table 2**, it can be seen that classification accuracy decreases with increasing number of classes. For example, when there are only 3 classes, the accuracy is 0.847, but it drops to 0.667 for 9 classes. One could say that the neural network's performance is influenced by the complexity of the classification task, but it's essential to consider the trade-off between the number of classes and model complexity. A higher number of classes often requires a more complex model or more training data to maintain high accuracy. The decrease in accuracy with more classes might be expected but should be weighed against the specific requirements and objectives of the application. Additionally, it can also be noted that he neural network is relatively better at assessing the General Aspect than other parameters. Furthermore, from **Table 3**, it can be noted that the obtained correlation of automated mineral content estimation varies across different minerals. For example, labNa has the highest correlation at 0.846, while labK has the lowest correlation at 0.634. This suggests that the automated method performs better for some minerals compared to others, which could be due to differences in the spectral signatures or the complexity of estimating each mineral. SPAD, NDVI, and LAI estimation shows high correlation, with values of 0.837, 0.941, and 0.953, respectively. This indicates that the automated approach is proficient in estimating these vegetation-related parameters, which are crucial for assessing plant health and growth. The correlation of Fresh biomass, Dry biomass, and moisture content estimation varies. This suggests that the automated method is particularly effective at estimating moisture content, which can be important for understanding plant hydration.

The results depicted in this paper suggest that the proposed framework is able to evaluate the turf visual aspect and estimate the mineral content as well as vegetation indices. Further investigation could involve fine-tuning the model architecture or exploring techniques such as data augmentation to improve accuracy, especially when dealing with a larger number of classes. Further investigation into the automated mineral content estimation, especially for minerals with lower accuracy, could involve data preprocessing techniques, feature selection, or the use of different machine learning algorithms. Additionally, for vegetation parameters and biomass estimation, the high accuracy indicates the potential for automation in agricultural or ecological monitoring tasks.

Table 2 Automated visual evaluation results

Number of classes	Neural network (Acc)			
	General Aspect	Leaf color	slenderness	uniformity of turfgrass
3	0,847	0,849	0,870	0,837
5	0,808	0,789	0,782	0,763
6	0,755	0,706	0,740	0,754
9	0,667	0,639	0,671	0,766

Table 3 Automated mineral content estimation results

labN	labP	labMg	labK	labNa	labCa	labZn	labFe	labMn	labCu
0,817	0,715	0,701	0,634	0,846	0,750	0,766	0,664	0,714	0,806

SPAD	NDVI	LAI	Fresh biomass	Dry biomass	moisture content
0,837	0,941	0,953	0,743	0,756	0,931

4. CONCLUSIONS

In this study, we have explored and analyzed the applicability of machine learning algorithms for the processing and analysis of remote sensing data. The provided data shows that the accuracy of the neural network is satisfactory and in average more than 70%. This result is promising considering the difficulty of the task. Furthermore, Automated mineral content estimation results provide valuable insights into the accuracy of automated mineral content estimation and the estimation of various other important parameters. The data can guide decisions on the suitability of automated methods for specific agricultural or environmental applications.

Based on the results analysis, we can confidently conclude that the proposed framework holds significant practical potential. It stands as a promising and reliable tool capable of supporting the crucial work of greenkeepers. This framework empowers greenkeepers with the means to assess the effectiveness of agrotechnical treatments in a more accurate and objective manner. Such a contribution is invaluable in the realm of turfgrass management, as it not only enhances the precision of evaluation but also streamlines decision-making processes, ultimately benefiting the overall quality and health of the turfgrass surfaces under their care.

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